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Landslide Susceptibility Analysis Using Open Geo-spatial Data and Frequency Ratio Technique

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Özet

Heyelan duyarlılık haritaları can ve mal kaybının en aza indirilmesi amacıyla mekansal karar vermede kullanışlıdır. Bu konuda, çeşitli yöntemler kullanılarak yapılmış birçok çalışma mevcuttur. Çoğunlukla, bu çalışmalar için gerekli olan mekansal veriler yerel kuruluşlar tarafından üretilmiştir ve küçük ölçekli çalışmalar için uygundur. Ancak lokal veriye erişimin olmadığı yada büyük ölçekli çalışmaların yapılacağı durumlarda kullanılmak amacıyla kıtasal/global veri setleri ile aktarılabilir ve ölçeklendirilebilir yaklaşımlar geliştirilmelidir. Bunun için, yerel kuruluşlar tarafından üretilmiş küçük ölçekli ve yüksek çözünürlüklü veri ile herkese açık ancak düşük çözünürlüklü verinin performanslarının karşılaştırılması önemlidir. Bu çalışmanın amacı bu karşılaştırma aracılığı ile herkese açık global verinin heyelan duyarlılık çalışmalarında kullanılabilirliğini incelemektir.

Bunun için Göta nehri vadisi (İsveç) ve Ruanda çalışma alanı olarak seçildi. Göta nehri vadisi kullanılarak lokal ve açık veri performanslarının karşılaştırılması yapıldı. Ruanda ise çalışmanın verimliliğinden ve başka bölgelere aktarılabilirliğinden emin olmak için analiz edildi. Çalışma için seçilen faktörler sırasıyla; yükseklik, eğim, toprak tipi, arazi örtüsü, yağış, litoloji, yola mesafe ve drenaj ağlarına mesafedir. Heyelan duyarlılık haritaları, Frekans Oranı yöntemi kullanılarak oluşturuldu. ROC eğrisi kullanılarak yapılan doğrulamada Göta nehri vadisi lokal ve açık veri analizleri ile Ruanda için sırasıyla 92.9%, 90.2% ve 83.1% doğruluk oranları elde edildi. Sonuçlar incelendiğinde yüksek çözünürlüklü lokal veriye erişimin olmadığı bölgelerde herkese açık global veri kullanımının yüksek bir potansiyel gösterdiği anlaşıldı.

Abstract

Landslide susceptibility maps are useful for spatial decision-making to minimize the loss of lives and properties. There are many studies related to the development of landslide susceptibility maps using various methods such as Analytic Hierarchy Process, Weight of Evidence and Logistic Regression. Commonly, the geospatial data required for such analysis (such as land cover and soil type maps) are only locally available and pertinent to small case studies. Transferable and scalable approaches utilizing publicly available, large scale datasets (ie., global or continental) are necessary to develop susceptibility maps in areas where local data is not available or when large-scale analysis is required. To develop such approaches, a systematic comparison between locally available, fine resolution, and larger scale, openly available but coarser resolution datasets is essential. The objective of this study is to investigate the efficiency of globally available public data for landslide susceptibility mapping by comparing it with the performance of the data provided from local institutions.

For this purpose, the Göta river valley in Sweden and the country of Rwanda were selected as study areas. Göta river valley was used for the comparison of local and open data. While Rwanda was used as a study area to ensure the efficiency of open data analysis and transferability of the framework. The selected landslide impact factors for this study are; elevation, slope, soil type, land cover, precipitation, lithology, distance to roads, and distance to drainage network. Landslide susceptibility maps were prepared by using the state-of-the-art Frequency Ratio method. The validation results using the prediction rate curve technique show 92.9%, 90.2%, and 83.1% area under curve values for local and open data analyses of Göta river valley and open data analysis of Rwanda country, respectively. The results show that globally available open data demonstrate strong potential for landslide susceptibility mapping when high-resolution local data are not available.

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Acronyms

FR: Frequency Ratio

GIS: Geographic Information System

LSM: Landslide Susceptibility Map

DEM: Digital Elevation Model

USGS: United States Geological Survey

NASA: National Aeronautics and Space Administration

SGU: Geological Survey of Sweden

ROC: Receiver Operating Characteristic

RMSE: Root Mean Square Deviation

AUC: Area Under Curve

SGI: Swedish Geotechnical Institute

MCDM: Multi-Criteria Decision Making

Contents

Chapter 1

Introduction

The term “landslide” is defined as the movement of rock, debris or earth, down in a sloped land [1]. Landslides occur when a down slope shear stress exceeds the shear strength of the slope [2]. They are considered as one of the most common natural disasters globally causing the death of hundreds of people and billions of dollars of property damages each year (Fig. 1.1) [3].

Figure 1.1: Landslides cause serious damages on lives and properties of people
(*Source: https://en.wikipedia.org/wiki/Landslide*)

The Global Landslide Catalog, prepared by NASA, shows the location of approximately 6000 landslides that occurred since 2007. According to the catalog, landslides caused more than 20,000 deaths between 2007-2015. The catalog shows that deadly landslides have mostly occurred in the parts of Asia and Southeast Asia [4]. In the 3rd of July 2021, a landslide hit a popular resort following a heavy rainfall in Atami city of Japan. It killed 2 people and left 20 people missing [5]. In India (state of Maharashtra), 23rd of July 2021, heavy rains triggered landslides and flooding. It caused the death of approximately 110 people [6]. More recently, in 3rd of January 2022, China witnessed a new landslide at a construction site in the southwestern region (Guizhou province). It left 14 people dead and 3 injured [7].

Natural disasters are more destructive in poorer countries than prosperous countries [8]. The death toll tends to be higher in a developing country than a developed country as a result of a natural disaster. In developing countries, people with lower income level have to live in unplanned settlements. In those areas, there is no municipal infrastructure. Therefore, they are more prone to natural hazards [9]. Additionally, in the long term, the process of repairing damages to roads and buildings take more time for developing countries [10]. Since buildings are poorly built, it is more difficult to survive for the people living in developing countries during a natural disaster. Other disadvantages is poor transport and communication systems as it is difficult for services to access remote and underdeveloped areas [11] .

In order to have a sustainable land use planning and reduce the loss of lives and properties, landslide susceptibility maps are needed [12]. Landslide susceptibility maps delineate the probability and spatial distribution of future landslides in a specific area based on specific influencing factors [13]. These factors frequently include steepness of the slope, deforestation, bedrock, type of soil, the amount of moist within the soil, distance to excavated areas [14]. The shear stress that causes landslide is dependent on these factors. One important factor is the degree of saturation of the soil. Precipitation and closeness to water sources make the soil saturated by increasing pore water pressure and decreases the shear strength. Therefore, the slope gets more susceptible for landslide occurrences. Land cover is another important factor since different types of areas have different level of susceptibilities and they need to be detected. For instance, deforested areas are more susceptible to landslides since the roots of trees are not strong enough to hold the soil when they are cut down [15]. The texture of the soil is also important to consider. Certain characteristics of soil such as the particle size, shape and pore distribution effect probability of landslide occurrence. Silted and/or clayey soils are known as more susceptible to landslides. For deeper landslides, lithological variety of the area needs to be considered since different rock units have different degrees of susceptibility. Moreover, excavation works decrease the load on topography and reduces the leakage of water. The areas closer to excavations are considered more susceptible. As the causal factors vary, landslides may occur in different ways (Fig. 1.2):

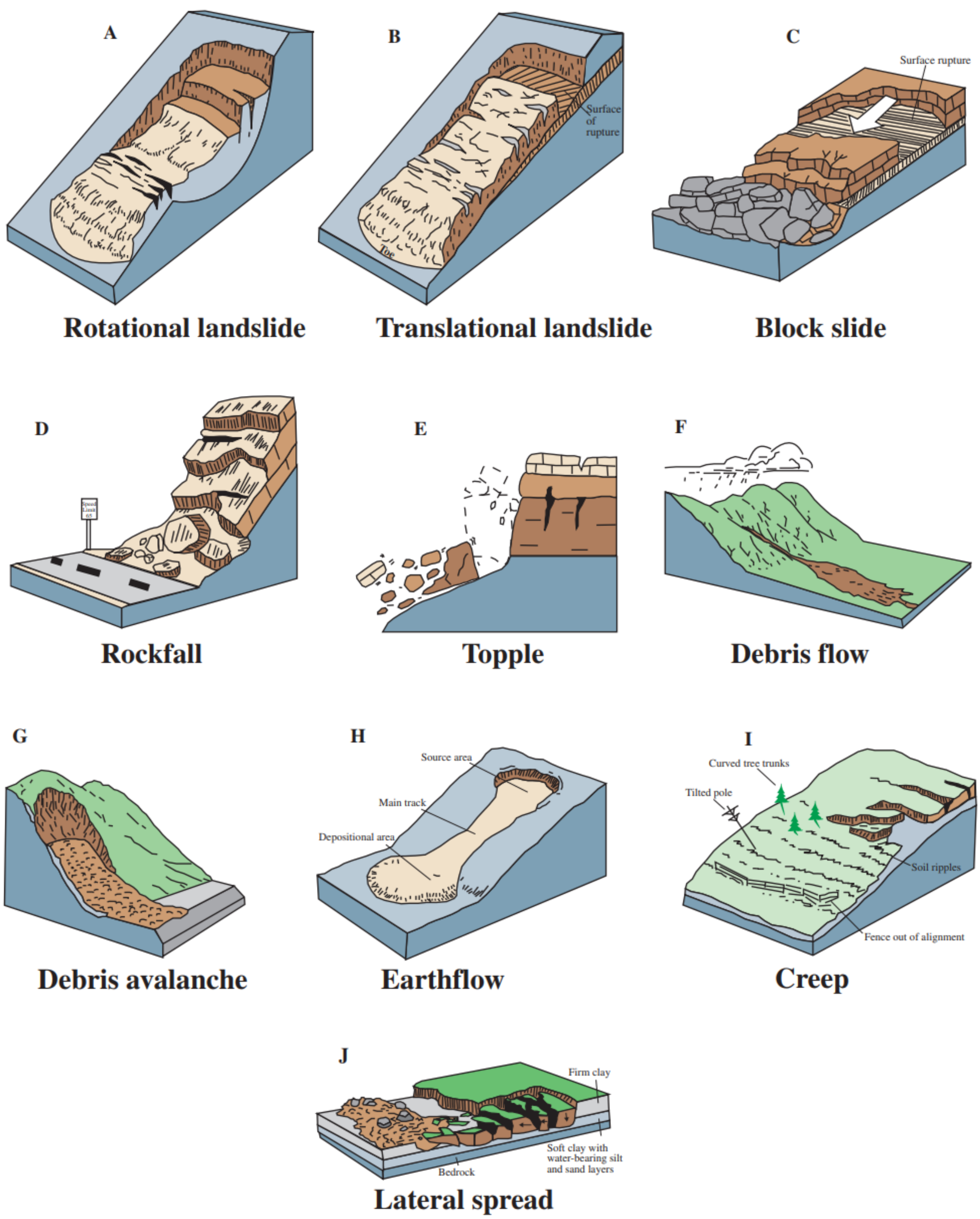


Figure 1.2: Major types of landslides
(<u>*Source:*</u> *U.S. Geological Survey,* <u>*Link:*</u> *https://pubs.usgs.gov/fs/2004/3072/pdf/fs2004-3072.pdf*)

Remote sensing data and techniques make it easier to develop landslide inventories and they are useful for understanding the spatial distribution and size of previously occurred landslides. It is also possible to assess the environmental characteristics that effect landslide susceptibility. Additionally, satellite-derived data sets can provide real-time information related to the landslide triggering events such as rainfall and earthquake [16].

As common geospatial tools have the capabilities to handle geospatial data (such as visualization, manipulation and analysis), landslide susceptibility mapping can be successfully performed. A frequent application of landslide mapping is through Geographic Information Systems (GIS), where it is possible to integrate the spatial data of different landslide influencing factors to detect landslide prone zones within a specified area [17].

Landslide susceptibility mapping is applied by researchers by using a wide range of heuristic, deterministic and statistical techniques such as Analytic Hierarchy Process, Logistic Regression and Machine Learning. One of the biggest challenges in the field is data availability. It may be difficult to find necessary data to prepare a landslide susceptibility map of a specific area. It was observed that, in most studies, the data required for landslide susceptibility mapping are collected from local institutions of a specific municipality or national organization, which makes applications over large areas, data scarce countries or in different geographical contexts a difficult task.

Accordingly, the aim of this study is to make a comparison of using open data and local data for landslide susceptibility analysis. A comparison will be made in the Göta river valley which is located in the Västra Götaland region of Sweden. Following, to ensure the robustness of the analysis, the whole Rwanda country will be analyzed afterwards using openly available data. The usage of open data for landslide susceptibility mapping will make spatiotemporal analysis easier to implement, particularly in areas with limited data availability. Additionally, information on the importance level of each criteria may increase accuracy levels of future studies.

Chapter 2

Literature Review

Landslide susceptibility mapping studies have been conducted for over 30 years by analyzing different areas and techniques. In this section, I perform a literature review on some of the most impactful studies in the field.

2.1 Methods for Landslide Susceptibility Analysis

By now, plenty of methods were used by researchers for landslide susceptibility analysis. Lee [18] investigated the number of studies that used each method for landslide susceptibility mapping in the period 1999-2018. According to the study, the methods that were used by researchers have heuristic or statistic approach, respectively. In this section, these approaches were presented.

2.1.1 Heuristic Approach

Heuristic approach uses opinions of experts who have deep knowledge related to geomorphology. Environmental factors are used as input and weighted according to the opinions of experts. This approach consists of two different analyses; direct mapping analysis and qualitative map combination. In direct mapping analysis, the susceptibility of the field is directly determined by the experts. In qualitative map combination, each class parameter within each causative factor is weighted by the experts. Since weights are determined directly by the experts, this approach is considered mainly subjective [19]. This approach is suitable for small scale regional analyses and mostly used by regional planning agencies [20]. Analytic Hierarchy Process is an example of heuristic approach.

2.1.2 Statistical Approach

Statistical approach provides results with higher objectivity compared to heuristic since the combinations of casual factors are statistically determined and landslide occurrences are quantitatively estimated. This approach requires landslide inventory data of the research area, consisting locations of previous landslides [19]. The factors are combined with the inventory data to predict the locations of future landslides [21]. This approach includes two different analyses; bivariate statistical analysis (e.g. Information Value, Weight of Evidence) and multivariate statistical analysis (e.g. Artificial Neural Network, Logistic Regression) [19]. In multivariate analysis, all conditioning factors are treated together. Bivariate analysis, in contrast, investigates the relationship of each factor with the landslide inventory separately [21].

2.1.3 Case Studies Using Different Methods

According to Lee's study [18], Logistic Regression was the most preferred method for the period of 1999-2008 and 2014-2018 while it was Frequency Ratio for the period of 2009-2013. Other methods such as Artificial Neural Network, Weight of Evidence, Analytic Hierarchy Process, Fuzzy Logic and Support Vector Machine were also popular among researchers regarding landslide susceptibility analysis. When the literature was checked for the period of 2019-2022, it was observed that the studies were mostly based on comparison of performances of different Machine Learning Techniques (e.g. Artificial Neural Network; Convolutional Neural Network, Random Forest, Decision Tree). In this subsection, some of the prominent studies were reviewed regarding the methods that were used and accuracy levels of the results.

Pourghasemi et al. [22] analyzed landslide susceptibility of Haraz watershed in Iran by using Weights of Evidence and Certainty Factor methods. For this purpose, a landslide inventory database that is used to assess the landslide susceptibility of the study area, with a total of 78 landslides, was mapped in the study area. The landslide data was randomly spilt into training and testing dataset. Of the 78 landslides identified, randomly 55 (70%) locations were chosen for the landslide susceptibility maps, while the remaining 23 (30%) cases were used for the model validation. The verification results showed that the weights-of-evidence model (79.87%) performed better than certainty factor (72.02%) model. It was indicated that in both of the models, the data acquisition and analysis were relatively easy and not very time consuming.

Pradhan [23] compared Frequency Ratio, Fuzzy Logic and Logistic Regression methods for analysis of Cameron catchment area in Malaysia. Validation was performed by comparing the known landslide location data with the landslide susceptibility maps. The rate curves were created and its areas of the under curve were calculated for all cases. In the case of frequency ratio model used, the area ratio was 0.8925 (i.e. the prediction accuracy is 89.25%). In the case of multivariate logistic regression model used, the area ratio was 0.8573 (i.e. the prediction accuracy is 85.73%). In the case of applying fuzzy algebraic "sum", the area ratio was 0.7531 (i.e. the prediction accuracy is 75.31%). Consequently, the case of frequency ratio model used showed a slightly higher accuracy than the fuzzy logic operators and multivariate logistic regression models.

Feizizadeh and Blaschke [24] analyzed landslide susceptibility of Urmia lake basin in Iran. The landslide susceptibility maps were produced based on weighted overlay techniques including Analytic Hierarchy Process (AHP), Weighted Linear Combination (WLC) and Ordered Weighted Average (OWA). Result of research indicated the AHP performed best in the landslide susceptibility mapping closely followed by the OWA method while the WLC method delivered significantly poorer results. However, accuracy levels of the result maps were not explained.

Devkota et al. [25] assessed landslide susceptibility of Mugling–Narayanghat road and its surrounding area using bivariate (certainty factor and index of entropy) and multivariate (logistic regression) models. 321 landslides were mapped and out of which 241 (75 %) were randomly selected for building landslide susceptibility models, while the remaining 80 (25 %) were used for validating the models. The validation of landslide susceptibility map was carried out using receiver operating characteristic (ROC) curves. The ROC plot estimation results showed that the susceptibility map using index of entropy model with AUC value of 0.9016 has highest prediction accuracy of 90.16 %. The susceptibility maps produced using logistic regression model and certainty factor model showed 86.29 and 83.57 % of prediction accuracy, respectively. It is concluded that all the models employed in the study showed reasonably good accuracy in predicting the landslide susceptibility of Mugling–Narayanghat road section.

Kavzoglu et al. [26] employed the Fuzzy Analytic Hierarchy Process and Support Vector Regression methods to assess the shallow landslide susceptibility of Trabzon province (NE Turkey). Performances of the methods were compared with that of widely used logistic regression model using ROC and success rate curves. Results showed that the Fuzzy-AHP and SVR outperformed the conventional logistic regression method in the mapping of shallow landslides. AUC values of the Fuzzy-AHP, SVR, and LR models were calculated as 0.9384, 0.9321, and 0.9108, respectively.

Yilmaz [27] applied and compared conditional probability (CP), logistic regression (LR), artificial neural networks (ANNs) and support vector machine (SVM) methods in Koyulhisar (Sivas, Turkey). AUC results for each method were 0.827, 0.831, 0.846 and 0.841, respectively. The results of the study showed that the maps obtained from SVM and ANN models looks like having a better accuracy than the conventional statistical methods; however, it was indicated that susceptibility maps can be easily produced using CP since input process, calculation and output processes are very simple in CP model when compared with the other methods considered in the study.

2.2 Commonly Used Factors

Different factors were used by different researchers in order to investigate landslide susceptibilities. There is not a standard rule regarding the selection of the factors. However, some factors were preferred by more researchers such as slope and land cover. On the table below, some of the outstanding studies in the field and the factors that were used within those studies were listed.

Further mentions: Slope [1], Precipitation [2], NDVI [3], Elevation [4], Soil Permeability [5], Land Cover [6], Distance to Roads [7], Distance to Drainage Network [8], Distance to Water Bodies [9], Curvature [10], Soil Type [11], Stream Power Index [12], Aspect [13], Lithology [14], Distance from Faults [15], Flow Direction [16], Soil Depth [17], Topographic Wetness Index [18]

Additionally, the studies were reviewed regarding data sources. Elevation map was mostly produced by extracting contour lines from topographic map of the study area. Slope, Aspect, Flow Direction, Curvature, Stream Power Index and Topographic Wetness Index maps were produced by using the Digital Elevation Model. Precipitation map was provided from the local meteorological agency. For satellite images, U.S. Geological Survey was preferred as data source. Land Cover and NDVI maps were prepared by using satellite images. Soil Permeability, Soil Type and Lithology maps were provided from the geology agency of the study area. Road, Drainage and Water Bodies data were provided from local public institutions or extracted from the topographic map of the study area. It can be seen that both local data and open data were used for landslide susceptibility studies. However, performances of local data and open data were not examined.

Table 2.2.1: The studies reviewed regarding factor selection and data sources

Research Study	Factors Used
Landslide susceptibility mapping using multi-criteria evaluation techniques in Chittagong Metropolitan Area, Bangladesh [28]	[1], [2], [3], [4], [5], [6], [7], [8], [9]
Application of a neuro-fuzzy model to landslide susceptibility mapping for shallow landslides in a tropical hilly area [29]	[1], [4], [7], [8], [10], [11], [12]
Application of an evidential belief function model in landslide susceptibility mapping [30]	[1], [2], [3], [4], [6], [7], [8], [10], [11], [12], [13], [14], [15]
Manifestation of an adaptive neuro-fuzzy model on landslide susceptibility mapping: Klang valley, Malaysia [31]	[1], [3], [4], [8], [10], [11], [15]
Application of likelihood ratio and logistic regression models to landslide susceptibility mapping using GIS [32]	[1], [3], [6], [8], [10], [11] [14],
GIS-based weights-of-evidence modelling of rainfall-induced landslides in small catchments for landslide susceptibility mapping [33]	[1], [6], [7], [11], [13], [16], [17]
Modification of landslide susceptibility mapping using optimized PSO-ANN technique [34]	[1], [4], [6], [7], [8], [10], [11], [12], [13], [14], [15]
Landslide susceptibility mapping at Hoa Binh province (Vietnam) using an adaptive neuro-fuzzy inference system and GIS [35]	[1], [2], [6], [7], [8], [10], [11], [13], [14], [15]
Landslide susceptibility mapping using ensemble bivariate and multivariate statistical models in Fayfa area, Saudi Arabia [36]	[1], [4], [7], [10], [11], [12], [13], [14], [15], [18]
Regional landslide susceptibility analysis using back-propagation neural network model at Cameron Highland, Malaysia [37]	[1], [2], [3], [6], [8], [10], [11], [13], [14], [15]

Chapter 3

Study Areas and Data

3.1 Study Areas

The first study area is the Göta river valley. It is located in the Västra Götaland region in Sweden. It is the largest river within the country with 90 km length between Vänern lake and Gothenburg city [38]. The study area covers 2724 km^2 and the highest elevation value within the area is 226 meters, according to the Digital Elevation Model provided by Lantmäteriet. According to the database prepared by the Swedish Geotechnical Institute, there are more than 200 previous landslides registered (`https://gis.swedgeo.se/skred/`). Considering the map, it can be said that the valley is one of the areas which has the highest susceptibility to landslides, within Sweden. One of the existing soil types within the area (and Sweden, in general) is quick clay and this soil type can make a landslide more widely spread and destructive [38]. Therefore, it was selected as a study area by also considering easy access to local data.

The second study area is the whole Rwanda country. It covers 26.338 km^2 area. The country is situated in East-Central Africa. The neighboring countries of Rwanda are; Uganda in the north, Tanzania in the east, Burundi in the south and Democratic Republic of Congo in the west [39]. There are high and steep mountains existing in northwest and central parts of the country [40]. The highest point is Volcan Karisimbi, with 4519 meters altitude. The lowest point is the Rusizi River, with 950 meters altitude [41]. According to the Digital Elevation model provided by the United States Geological Survey, the lowest elevation value is 921 meters while highest value is 4500 meters. The global landslide inventory map, provided by NASA, shows that landslides are quite common in the area. Considering its relatively smaller size and poor local data availability, it was selected as the second study area.

3.2 Data

3.2.1 Landslide Inventory Maps

To train the models and validate the results of analyses, locations of previous landslides were needed. Landslide data for Göta River valley was provided from SGU (Geological Survey of Sweden). To get landslide data for Rwanda, the global landslide database of NASA was used. NASA Global Landslide Viewer portal provides information related to landslides previously occurred around the world. Figure 3.2.1 shows locations of previous landslides, which occurred around the Göta river. Landslides are represented as lines and they were converted to points afterwards, for validation of susceptibility maps. Figure 3.2.2 shows previous landslide locations that occurred in Rwanda. Since there is no landslide recorded for Göta river valley in NASA Landslide Viewer portal, the one provided from SGU was used for analysis and validation of both local data analysis and open data analysis of Göta river valley. Both local inventory and open inventory were checked for the occurrence dates of the landslides. It was seen that SGU did not include this information within the data and on the website (https://sgu.se/). On the contrary, the occurrence date of each landslide was indicated within NASA Global Landslide Catalog. According to the catalog, occurrence dates of the landslides within Rwanda ranges between 2010-2018.

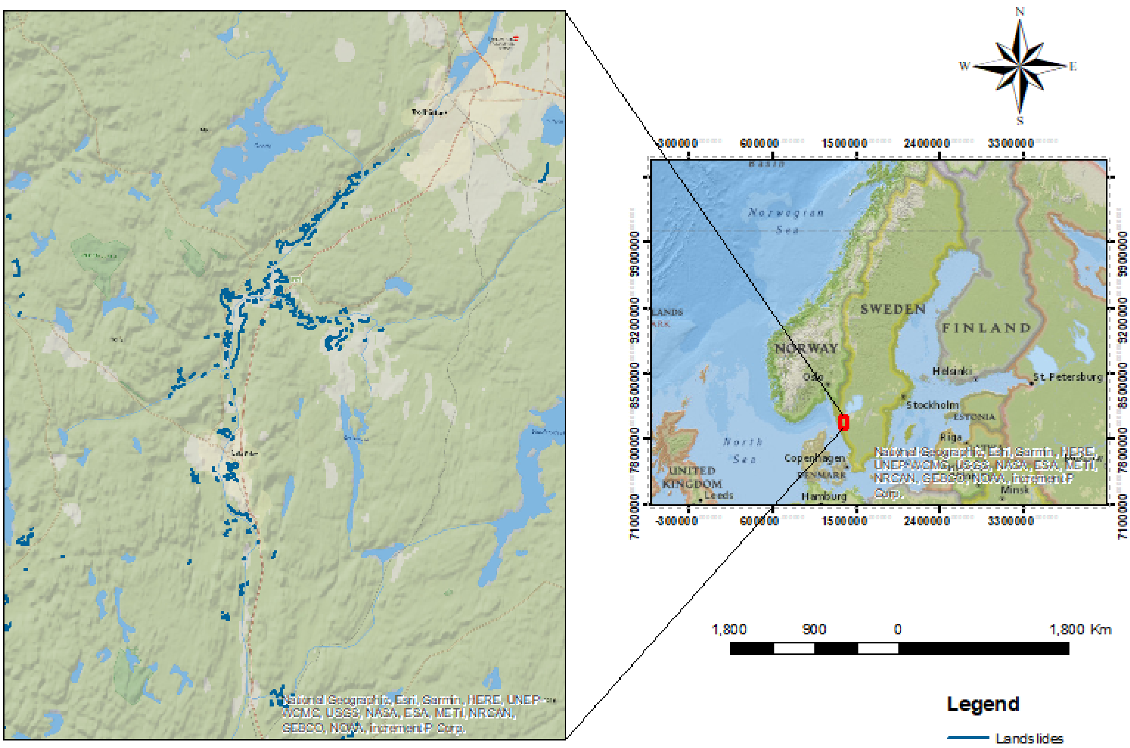


Figure 3.2.1: Landslide Inventory Map of Göta River Valley

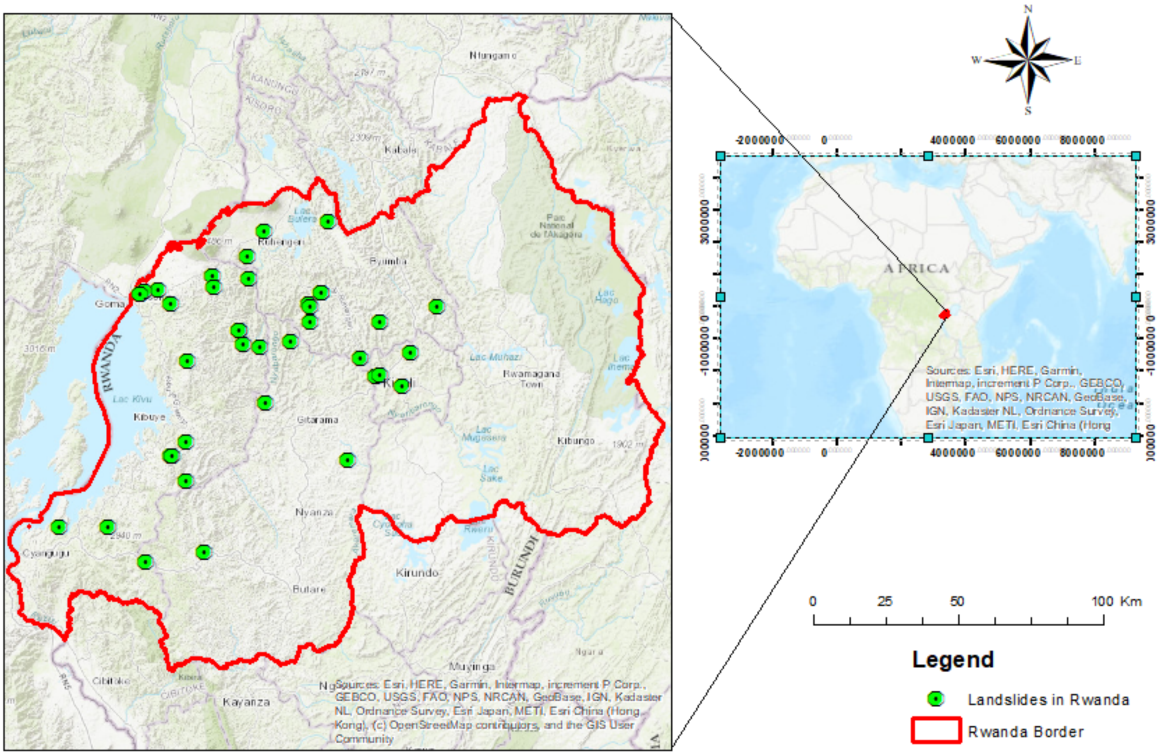


Figure 3.2.2: Landslide Inventory Map of Rwanda

3.2.2 Spatial Resolution Issue

The term "spatial resolution" is used to state the number of pixels that construct a digital image [42]. It is important since it affects the level of sharpness in an image [43]. Further, it needs to be considered when doing landslide susceptibility analysis of an area since it may affect the accuracy of the result map. Since ArcGIS will be used for this study, the website of the software is reviewed for this issue. In the article named "Cell size and resampling in analysis", it is indicated that the ideal situation is that all data have the same spatial resolution. However, if they have different spatial resolution values, then they will be automatically resampled to the coarsest resolution [44].

Chen et al. [45] investigated the effect of spatial resolution on the accuracy of landslide susceptibility analysis. 7 different resolution values were tested (30, 40, 50, 60, 70, 80 and 90m) in the Baxie River basin in China. They used frequency ratio, index of entropy, and weight of evidence methods for the analyses. They found out that the highest accuracy could be obtained by using 70 meter resolution input data. This result shows that higher spatial resolution does not necessarily provide more accurate results.

Lee et al. [46] analyzed the Boun region of Korea. 15 factors were used with 4 different resolution values (5, 10, 30, 100 and 200m). They found that analyses with 5, 10 and 30 meter resolution values provide similar results. However, 100 and 200 meter resolutions provided lower accuracy. It is indicated that this difference arises from the scale values. The scale of the input data was 1:5000 - 1:50000. For this scale range, at least, less than 30m resolution is needed, according to the study.

Meena and Nachappa [47] searched for the effects of different spatial resolution values in Kullu Valley, Himalayas. 12.5 meter, 30 meter and 90 meter digital elevation models are used within the study. Frequency Ratio method is applied for landslide susceptibility mapping. According to the results, 30 meter DEM showed higher accuracy (0.910) compared to 12.5 meter model (0.839) and 90 meter model (0.824).

Pradhan and Sameen [48] used 15 factors and 9 different spatial resolution values (0.5, 1, 2, 3, 5, 10, 20, 30 (LIDAR-based) and 30 meter (ASTER-based)). By applying the Logistic Regression method, the 3 meter elevation model provided the most accurate result. It is indicated that, may be a better choice for land use planning and slope management since susceptibility zones can be accurately extracted at the parcel level.

According to the existing literature, it is observed that there is still not a certain case and a clear explanation related to the spatial resolution/scale issue. Its effect may depend on other conditions such as the size of the area and the scale of the input maps. For this reason, the effect of spatial resolution on the accuracy level of landslide susceptibility mapping was ignored in this study. All of the analyses were completed in 50m x 50m resolution.

3.2.3 Factors

8 factors were used in this study for 3 different analyses; Göta river valley local data analysis, Göta river open data analysis and Rwanda open data analysis. On the tables below, the information related to the factor maps were listed. They were separated as Göta river valley data and Rwanda data. However, for Göta river open data analysis, same data sources were used with Rwanda.

Table 3.2.1: Data information were listed for each factor for the Göta river valley

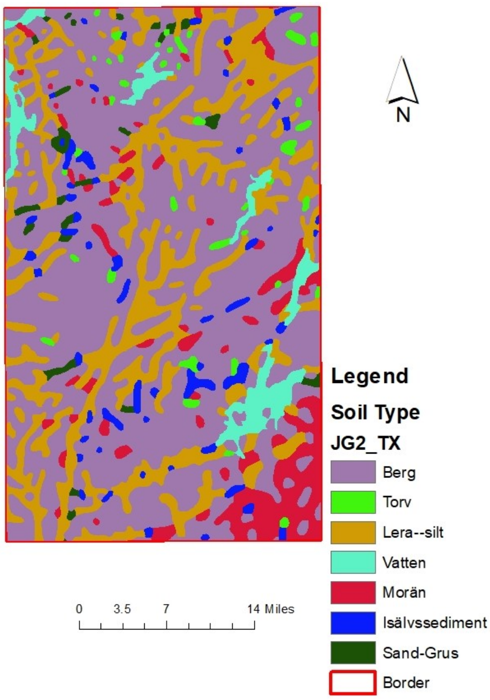
Parameter	**Data Type**	**Data Source**	**Spatial Resolution**
Elevation	Raster	Lantmäteriet	50m
Soil Type	Vector (Polygon)	SGU	-
Slope	Raster	Lantmäteriet	50m
Distance to Roads	Vector (Line)	Trafikverket	-
Lithology	Vector (Polygon)	SGU	-
Distance to Drainage	Vector (Line)	Lantmäteriet	-
Land Cover	Raster	Lantmäteriet	10m
Precipitation	Vector (Point)	SMHI	-

Table 3.2.2: Data information were listed for each factor for Rwanda

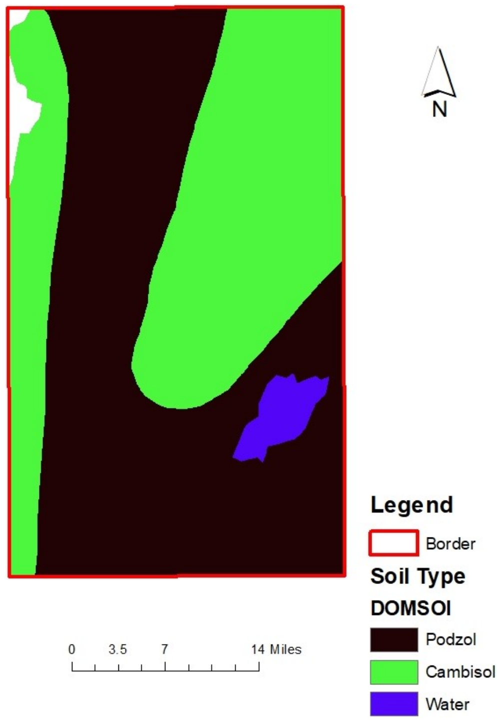
Parameter	Data Type	Data Source	Spatial Resolution
Elevation	Raster	USGS	30m
Soil Type	Vector (Polygon)	FAO	-
Slope	Raster	USGS	30m
Distance to Roads	Vector (Line)	OpenStreetMap	-
Lithology	Vector (Polygon)	Hamburg University	-
Distance to Drainage	Vector (Line)	OpenStreetMap	-
Land Cover	Raster	ESRI	10m
Precipitation	Raster	University of East Anglia	200m

Soil Type

Slope stability is influenced by certain characteristics of soil such as particle size, shape and pore distribution. Compared to the coarser textured soils, finer-textured soils (which include smaller particles such as silt and clay) can hold larger volumes of water and have a larger surface area. Increasing pore pressure makes the soil weaker [49]. Soil maps were provided in vector format from SGU (Geological Survey of Sweden) for the local data analysis and from FAO (Food and Agricultural Organization of the United Nations) for the open data analyses (Fig. 3.2.3, 3.2.4). They were rasterized afterwards. The local data provided from SGU (Geological Survey of Sweden) has different soil classes compared to the one provided from FAO (Food and Agriculture Organization). The classes of the SGU map include Berg (mountain), Torv (peat), Lera–silt (silted and/or clayey soil), Vatten (water), Morän (moraine), Isälvssediment (ice river sediment) and Sand-Grus (sand-gravel). The FAO map classified the soils according to the particles they include and named them in a different way (e.g. Podzol, Cambisol, Nitosol, Andosol). According to the SGU map and the landslide inventory of Göta river valley, Berg(mountain) areas have experienced 40 landslides and the areas with Postglacial soil have 5. Most of the landslides (235) have occurred in the areas with Lera–silt (silted and/or clayey) soil type while Isälvsediment (ice river sediment) and Morän (moraine) classes have only 2 landslides. There is no landslide occurred in the rest of the classes. According to the FAO soil map, 192 of the 284 landslides have occurred in the areas with Podzol soil in the Göta river valley and the rest is within Cambisol soil. In Rwanda, almost 2/3 of the landslides (23) have occurred within Nitosol soil. Ferralsol and Andosol soils have 6 landslides while Lithosol has 3 and Cambisol has only 1.



(a) Soil map of Göta river valley provided from SGU



(b) Soil map of Göta river valley extracted from Global Soil Map of FAO

Figure 3.2.3: Soil maps of Göta River Valley provided from different sources

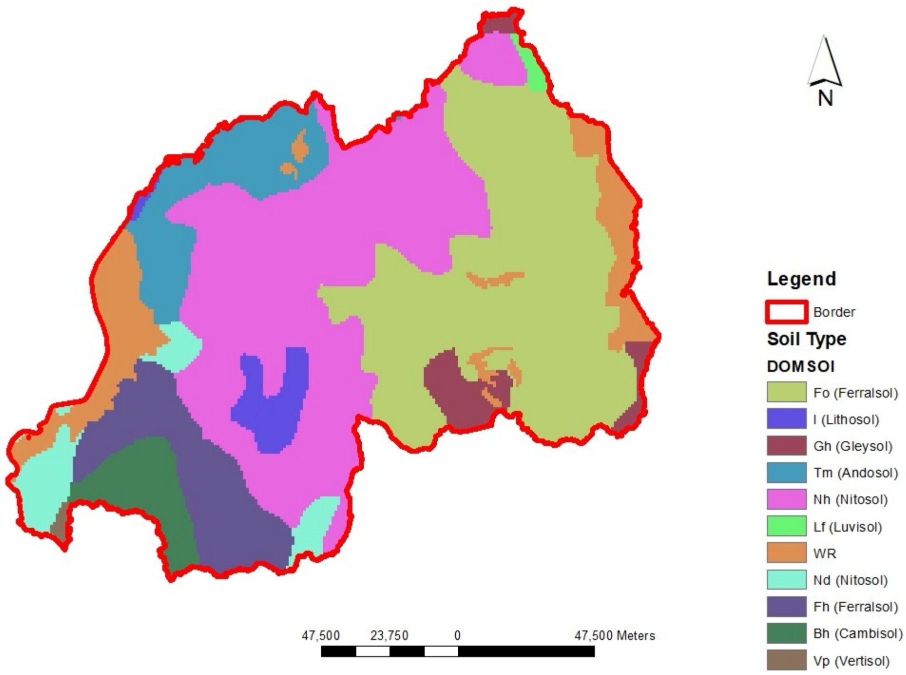
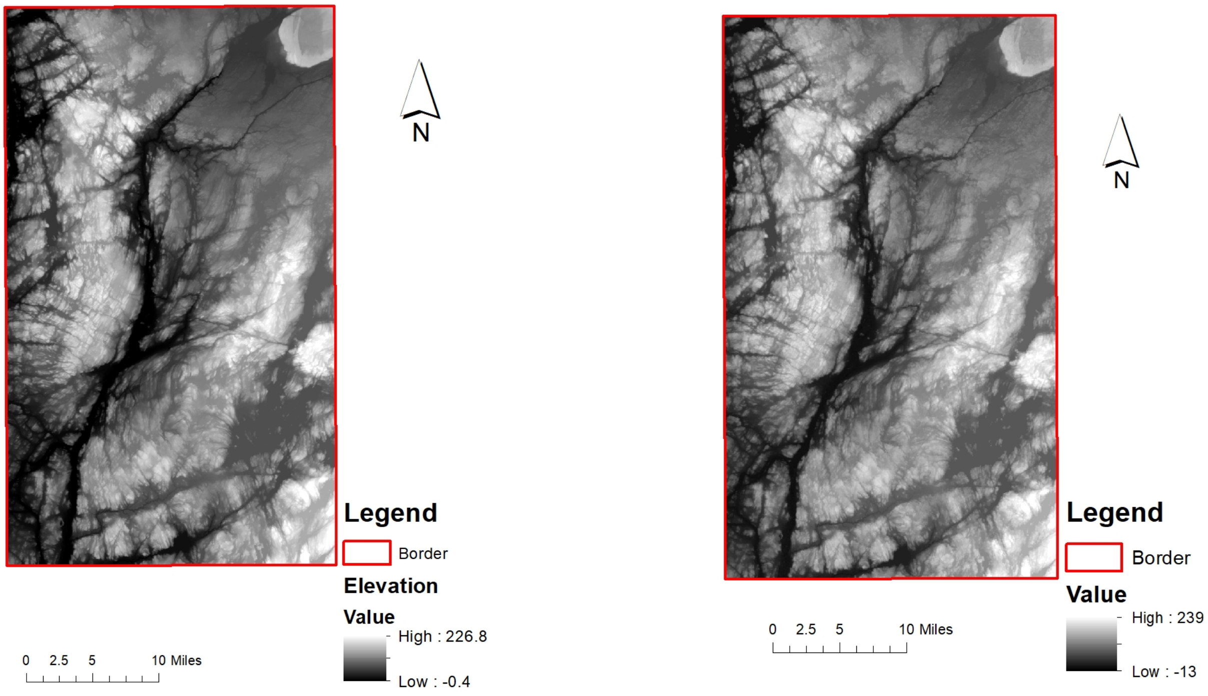


Figure 3.2.4: Soil Map of Rwanda provided from FAO

Elevation

Elevation is one of the indirect contributors to the landslide occurrence with relation to the other parameters such as tectonics and precipitation [50]. At very high elevations, mountain peaks worn by different rock types and higher shear force is making it less susceptible to landslide occurrences. Materials coming from higher elevations make intermediate elevations more prone. Lower elevations are also less susceptible to landslides due to less slope angle values and thick vegetation cover [51–53]. The Digital Elevation Models were provided from Lantmäteriet (The Swedish Mapping, Cadastral and Land Registration Authority) for the local data analysis and from USGS (United States Geological Survey) for the open data analyses (Fig. 3.2.5, 3.2.6). The DEM provided from Lantmäteriet has 50 meter spatial resolution while the models provided from USGS have 30 meter resolution. In addition to the 50 meter resolution DEM, another Lantmäteriet DEM with 2 meter pixel size was also available. However, 50 meter DEM was used for the analysis to speed up the analysis process. Lantmäteriet DEM was produced in 2012 while USGS DEMs were produced in 2014. Within both local and open elevation maps of the Göta river valley, it was observed that approximately 210 of the landslides have occurred in the areas with lower than 40 meter elevation. The areas that have an elevation between 40 - 70 meters, have experienced 65 landslides. 9 landslides were observed within the 70 - 100 m interval while there is only 1 landslide occurred between 100 - 130 meter and not any landslide in the areas with more than 130 meter elevation. Within Rwanda, there are only 2 landslides observed within 920 - 1500 meters interval. The areas with 1500 - 1730 meters elevation has experienced the most number of landslides (15) followed by 3rd class (1730 - 2000 meters interval). 8 landslides were observed within the 4th class (2000 - 2350 meters) while only 3 landslides have occurred in the areas that have an elevation between 2350 - 4500 meters. Classification of the elevation maps was completed by using Natural Breaks classification method.



(a) Lantmäteriet Elevation Map

(b) USGS Elevation Map

Figure 3.2.5: Elevation Maps of Göta River Valley Provided from Different Data Sources

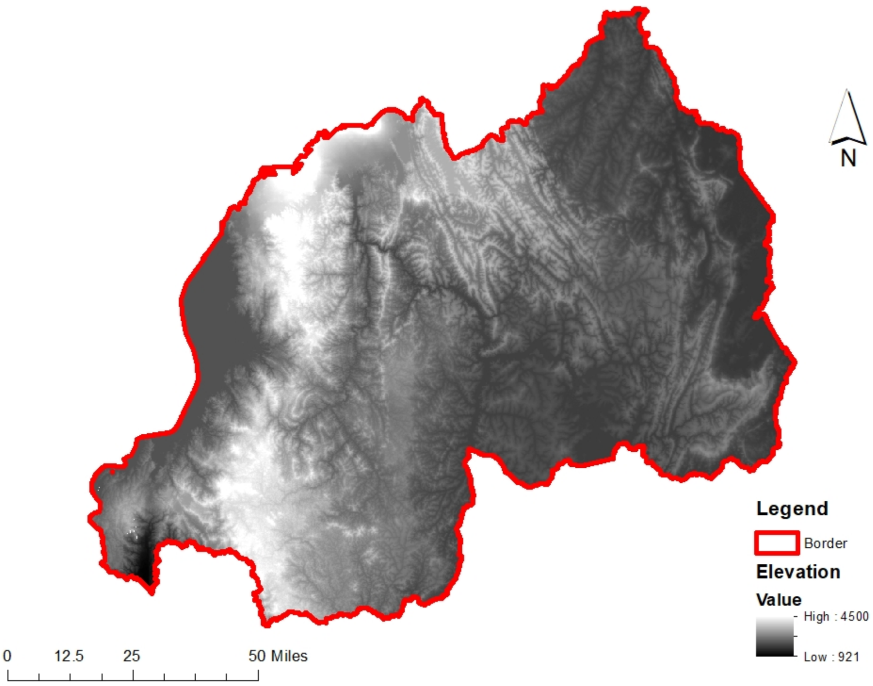


Figure 3.2.6: Elevation Map of Rwanda

Slope

Slope angle is one of the important factors for landslide susceptibility mapping. According to the factor statistics, it is the factor that is commonly used by researchers [54]. It has a direct relationship with landslide occurrences [55]. After precipitation, flow rate of the surface and the moisture content in the soil depend on the degree of slope [56]. If slope degree is very low, then the possibility of a landslide occurrence is low. It becomes very high as the slope degree increases to moderate values. However, the susceptibility is moderate in high and very high slope degree values [57]. Slope maps were produced from Digital Elevation Models by using ArcGIS software for each of the analyses and they were reclassified with Natural Breaks classification method (Fig. 3.2.7, 3.2.8). In the Göta river valley, most of the previous landslides (149) have occurred in the areas with 2° - 5° slope angle. In the areas with lower than 2° slope, there are 27 landslides observed. 86 landslides fell into 5° - 8° while 19 landslides can be seen in the areas with 8° - 14° slope. The areas with higher slope angle than 14° have experienced only 2 landslides. Within Rwanda, it was observed that there is closer relationship with higher slope degrees and landslide occurrences. There are 7 landslides occurred in the areas with 0° - 5° slope angle and 6 landslides were observed in 5° - 11°. 11 landslides fell into 11° - 18° class while 12 landslides occurred in 18° - 27° slope angles. There are only 3 landslides occurred in the areas with higher slope angle than 27°.

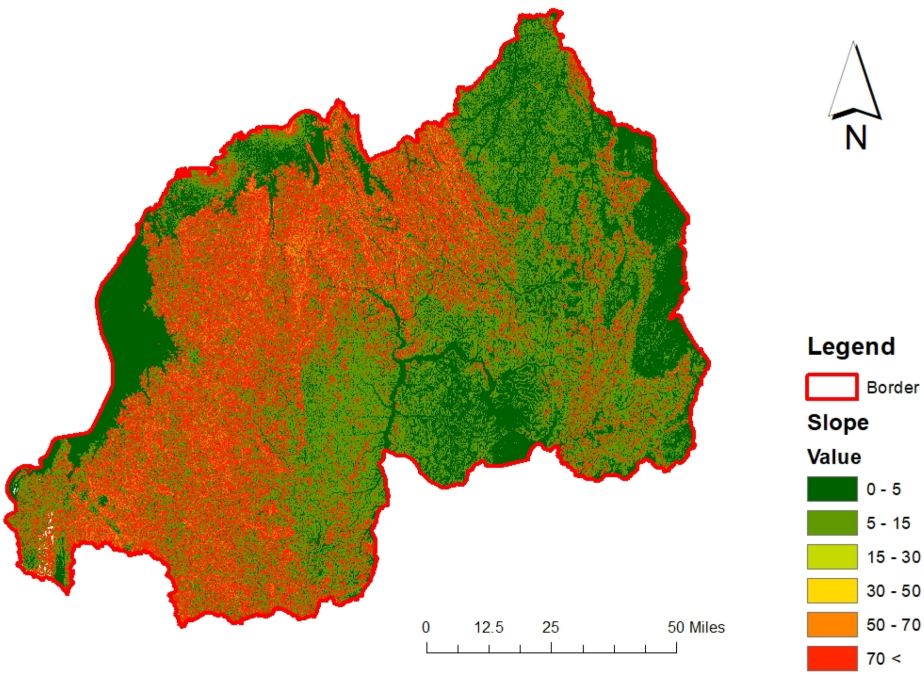
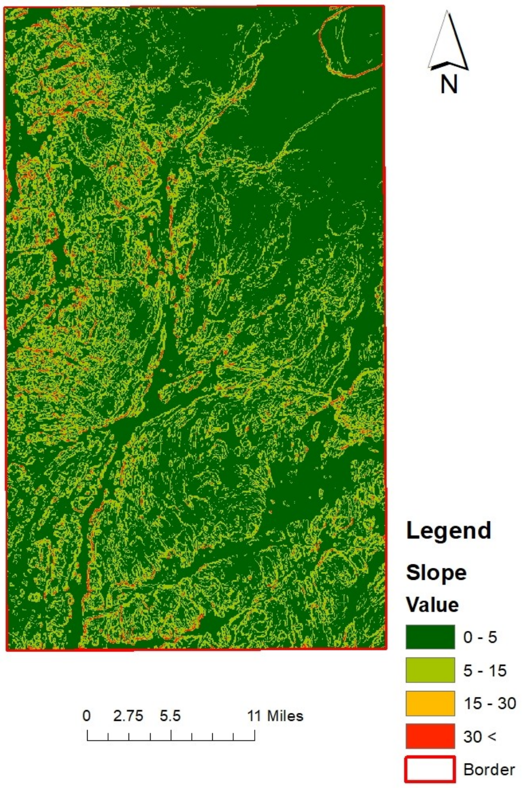
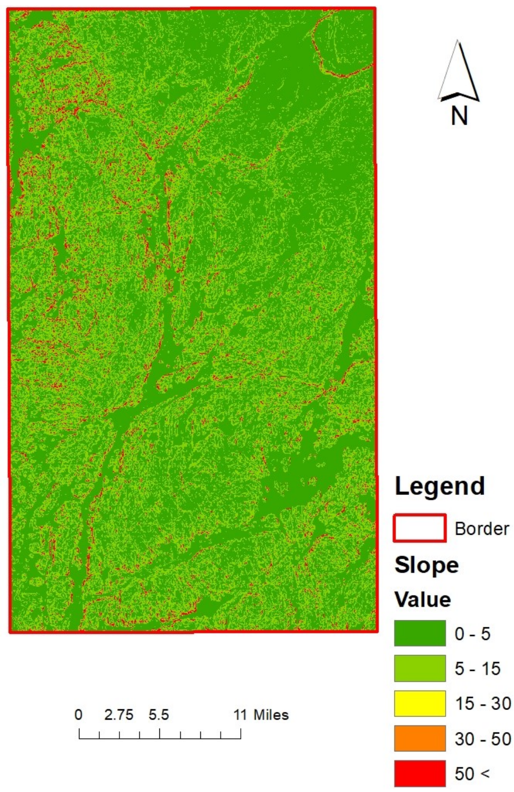


Figure 3.2.7: Slope Map of Rwanda



(a) Slope map produced by using Lantmäteriet DEM

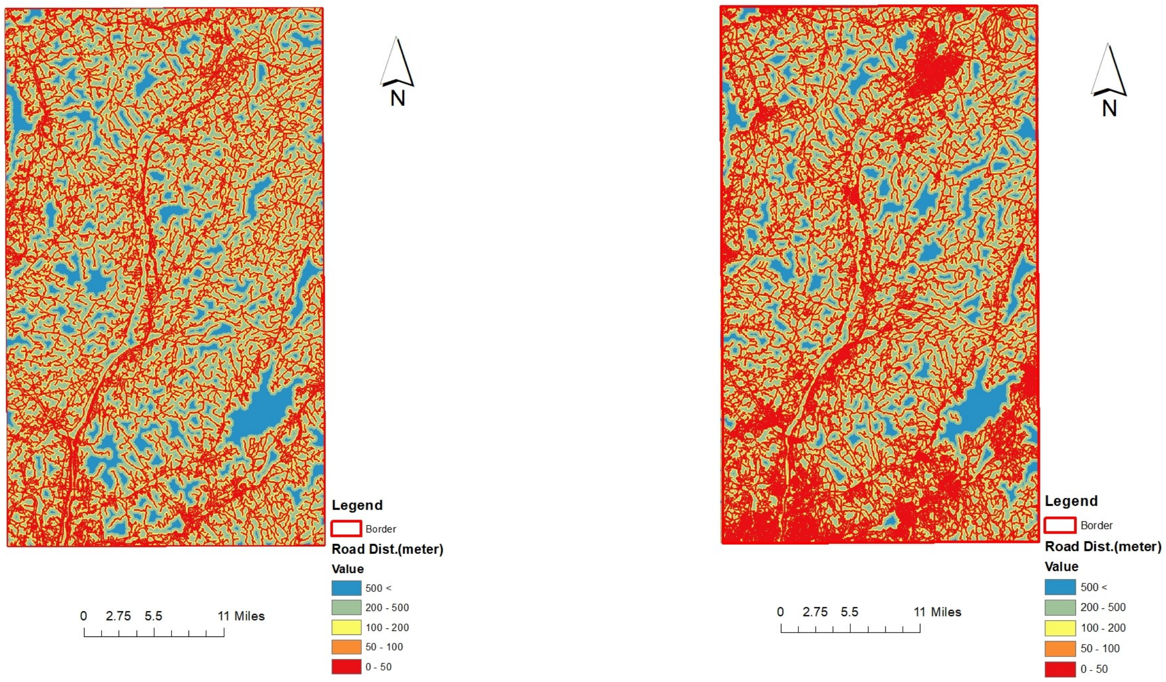


(b) Slope map produced by using USGS DEM

Figure 3.2.8: Slope maps of Göta River Valley produced by using DEMs from different data sources

Distance to Roads

Since excavation is needed for construction of roads, it may create instability on the slopes near the roads by decreasing the load on topography and reducing the leakage of water [54, 58]. Roads can often cause landslides with major damages [54]. Additionally, vibrations made by vehicles that pass on the roads increase the possibility of landslide occurrence [56]. It is selected as conditioning parameter by many researchers for landslide susceptibility analysis [54]. Road shape file data were provided by Trafikverket (Swedish Transport Administration) for local data analysis and OpenStreetMap for open data analyses (Fig. 3.2.9, 3.2.10). Distance to road maps with 50 meter resolution were prepared by using Euclidean Distance tool in ArcGIS. This factor was divided into 5 different buffer ranges for Göta river valley (0-100m, 100-250m, 250-500m, 500-750m, >750m) and 2 different buffer ranges for Rwanda (0-100m, >100m), based on existing literature and locations of previous landslides. In the Göta river valley, 134 of the previous landslides are located in the areas that are closer than 100m to the roads. In 100-250m interval, 120 landslides occurred and 29 landslides fell into 3rd class, 250-500m. There are no landslides in areas more than 500m away from the roads. In Rwanda, 37 of the 39 previous landslides are located in the areas that are less than 100 meter away from the roads.



(a) Distance to Roads map produced by using Trafikverket road data

(b) Distance to Roads map produced by using OpenStreetMap road data

Figure 3.2.9: Distance to Roads maps of Göta River Valley produced by using road data from different data sources

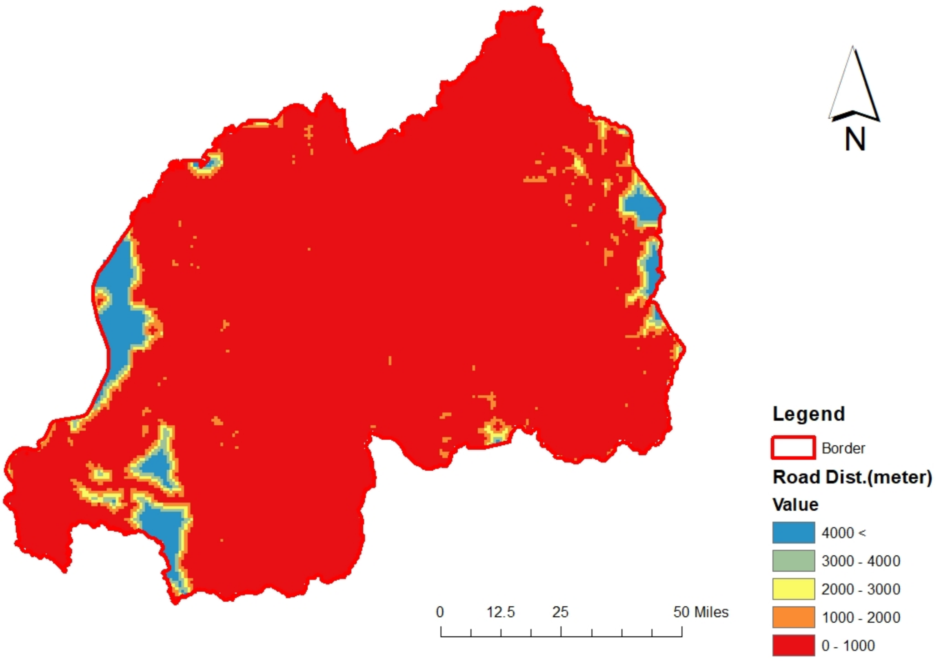


Figure 3.2.10: Distance to Roads Map of Rwanda

Lithology

Lithological characteristics of the area is widely accepted as a main landslide conditioning parameter by researchers [54]. Since different rock units have different degrees of susceptibility, it effects the slope instability and landslide occurrence [59, 60]. The lithology map of the Göta river valley were provided from SGU, The Geological Survey of Sweden for local data analysis (Fig. 3.2.11). For the open data analyses, the maps were extracted from the Global Lithological Map of Hamburg University Institute for Geology (Fig. 3.2.12, 3.2.13). The local lithology map consists of 24 classes; ”Tonalit-granodiorit”, ”Granit”, ”Granodiorit-granit”, ”Kvartsarenit (Quartz arenite)”, ”Paragnejs (Paragneiss)”, ”Ultrabasisk intrusivbergart (Ultrabasic intrusive rock)”, ”Anortosit (Anorthosite)”, ”Gabbroid-dioritoid”, ”Monzodioritisk-granodioritisk gnejs”, ”Vacka (Greyhound)”, ”Sandsten (Sandstone)”, ”Granodioritisk-granitisk gnejs”, ”Ytbergart (Supracrustal rock)”, ”Ögongnejs (Eye gneiss)”, ”Tonalitisk-granodioritisk gnejs”, ”Dacit-ryolit”, ”Gnejs”, ”Diabas (Diabase)”, ”Skiffer (Schist)”, ”Basalt-andesit”, ”Granitoid-siyenitoid”, ”Granitisk gnejs”, and ”Leukogranitisk gnejs”. The global lithological map is more generalized and includes 5 classes for this area. These classes include; ”Metamorphic Rocks”, ”Acid Volcanic Rocks”; ”Acid Plutonic Rocks”, ”Siliciclastic Sedimentary Rocks” and ”Intermediate Volcanic Rocks”. The same map has 4 classes for Rwanda; ”Unconsolidated Sediments”, ”Basic Volcanic Rocks”, ”Water Bodies” and ”Metamorphic Rocks”.

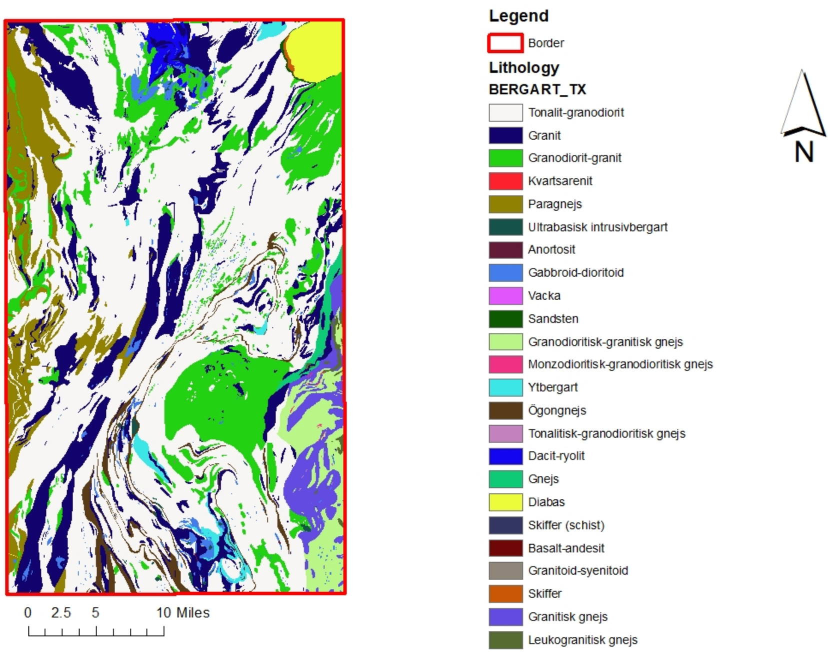


Figure 3.2.11: Lithology map of the Göta river valley provided from Geological Survey of Sweden

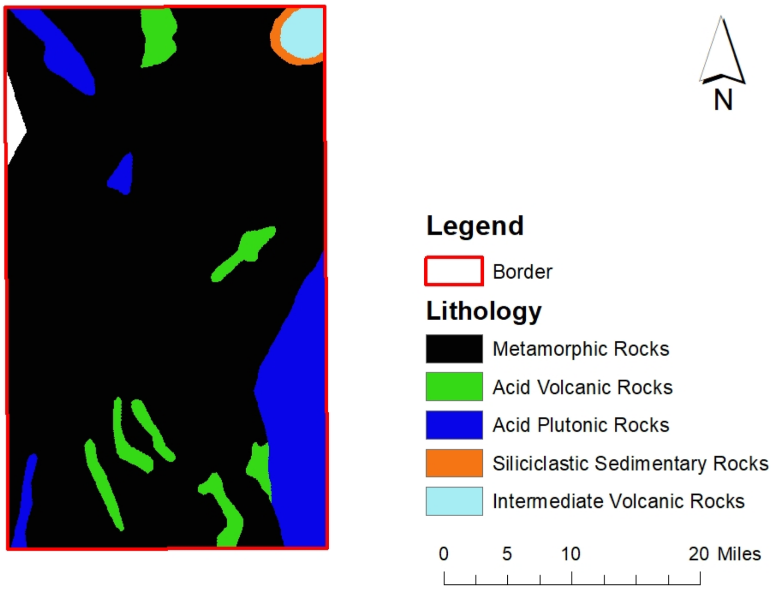


Figure 3.2.12: Lithology map of the Göta river valley provided from Geology Institute of Hamburg University

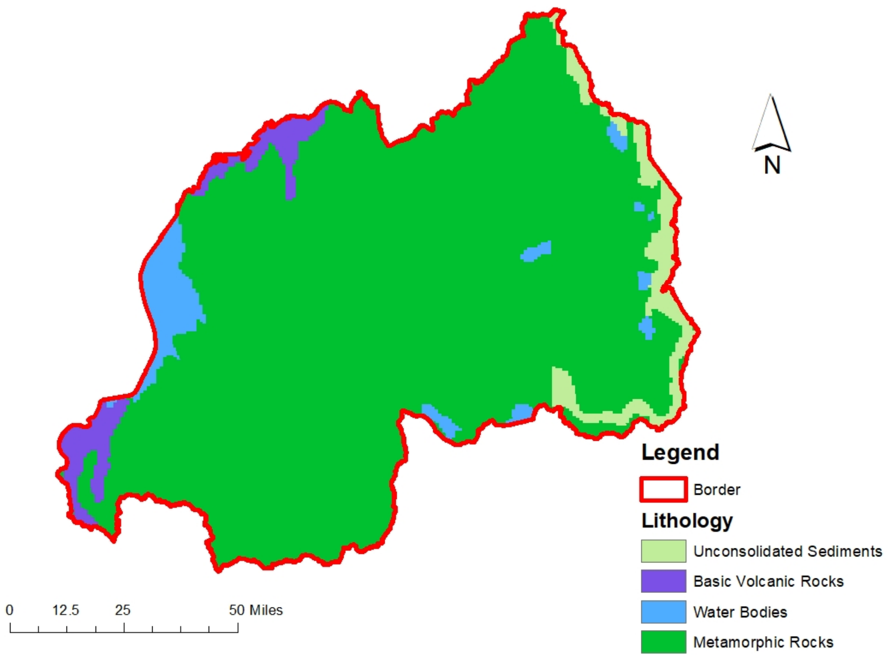


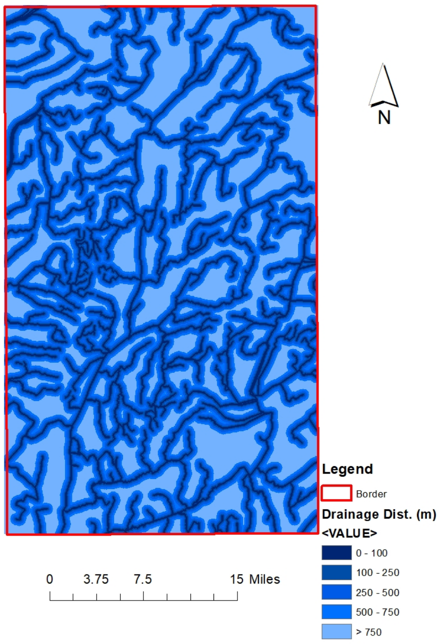
Figure 3.2.13: Lithology Map of Rwanda provided from Geology Institute of Hamburg University

According to the lithology map provided from SGU, 225 of the previous landslides occurred in the areas that have ”Tonalit-granodiorit” rock type. ”Granodiorit-granit” and ”Ögongnejs” classes experienced 9 landslides while there are 5 landslides in ”Paragnejs” and 4 landslides in ”Gabbroid-dioritoid”. According to the Global Lithological Map, in the Göta river valley, 276 of the landslides occurred in ”Metamorphic Rocks”. 7 landslides are located in ”Acid Plutonic Rocks” and there is only 1 landslide in ”Acid Volcanic Rocks”. In Rwanda, 36 of the 39 landslides occurred in ”Metamorphic Rocks” while there are only 3 landslides in ”Basic Volcanic Rocks”.

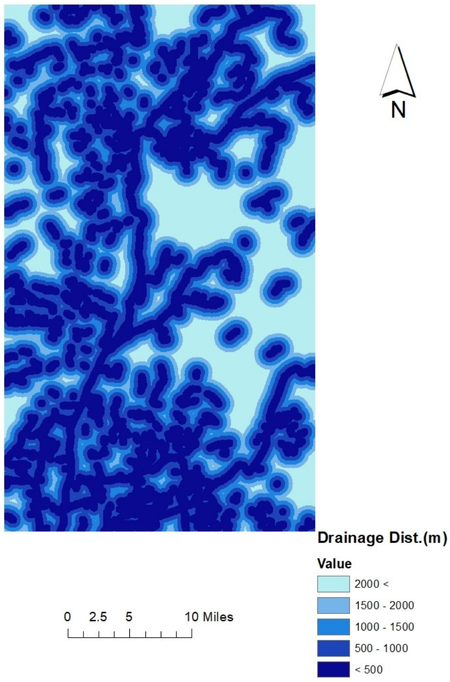
Distance to Drainage

Saturation degree of the soil is important to consider and effective on landslide occurrences. As proximity to drainage structures decreases, the slope material gets saturated and it becomes more susceptible for landslide occurrences. Additionally, the increase in pore water pressure leads erodes on slopes and decreases soil shear strength [61, 62].

For local data analysis, the drainage network was provided from SMHI (Swedish Meteorological and Hydrological Institute), (Fig. 3.2.14). For open data analyses, drainage network data were provided from OpenStreetMap (Fig. 3.2.14, 3.2.15). Afterwards, distances to drainage networks were calculated. This factor was divided into 5 different buffer ranges for Göta river valley (0-100m, 100-250m, 250-500m, 500-750m, >750m) and 2 different buffer ranges for Rwanda (0-100m, >100m), based on existing literature and locations of previous landslides. In the Göta river valley, 102 landslides are located in the areas that are closer than 100 meters to the drainage network. Within 100m - 250m interval, there are 111 landslides observed. After 250 meters, the number of landslides decreased as the distance increased. 28 landslides were observed in 250m - 500m interval while 23 in 500m - 750m and 20 in >750m. In Rwanda, 22 landslides occurred in the areas that are closer than 100 meters to the drainage network.



(a) Distance to Drainage Network map provided from Swedish Meteorological and Hydrological Institute



(b) Distance to Drainage Network map provided from OpenStreetMap

Figure 3.2.14: Distance to Drainage Network maps of Göta River Valley provided from different data sources

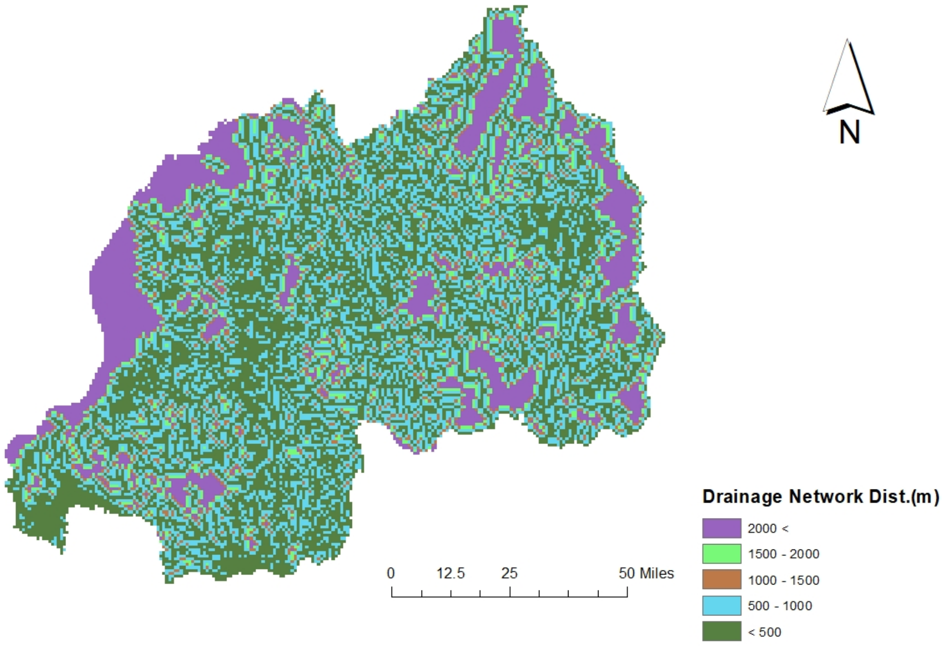


Figure 3.2.15: Distance to Drainage Network Map of Rwanda

Land Cover

Land cover is the factor that has both positive and negative effects on landslide occurrences [60]. Compared to the other factors, land cover is the one that is most connected to human activities. Therefore, it is more possible to manage and change the land cover of an area [63]. Different land cover types have different degrees of susceptibility. Vegetated areas are considered less susceptible since plants absorb the water within the soil and make the slope stronger with their roots [61]. On the contrary, barren areas are more susceptible to landslides [64]. For open data analyses of the Göta river valley and Rwanda country, land cover maps were extracted from ESRI Global Land Cover Map (Fig. 3.2.16, 3.2.17). For local data analysis of the Göta river valley, land cover map was provided from Lantmäteriet (Fig. 3.2.17). Lantmäteriet land cover map was produced in 2012 and updated in 2018 by comparison between satellite images from 2012 and 2018 respectively. ESRI land cover map was produced by using the entire Sentinel-2 scene collection for each year from 2017 to 2021. It was indicated on the website that more than 2,000,000 Earth observations from 6 spectral bands were used with Artificial Intelligence training models to produce the maps [65]. Lantmäteriet land cover map contains more detailed classes compared to ESRI land cover map (it includes around 35 classes). These classes were generalized for a better comparison with ESRI land cover map as follows; 'Water Body', 'Built-up Area', 'Swamp', 'Sandy Area', 'Agricultural Land', 'Bush', 'Barren Land' and 'Forest'. Differently, ESRI land cover map does not contain 'Sandy Area' class.

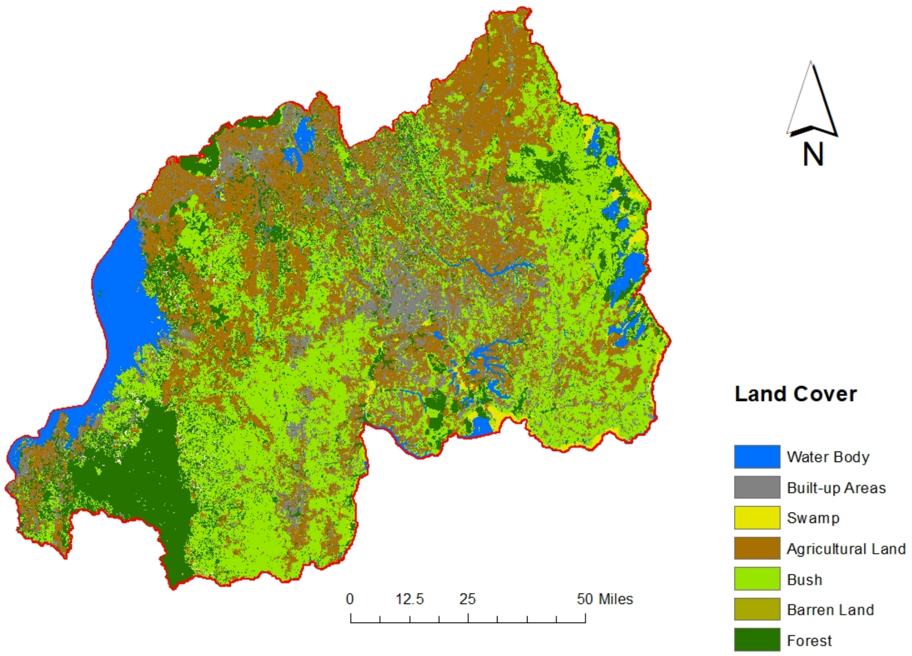
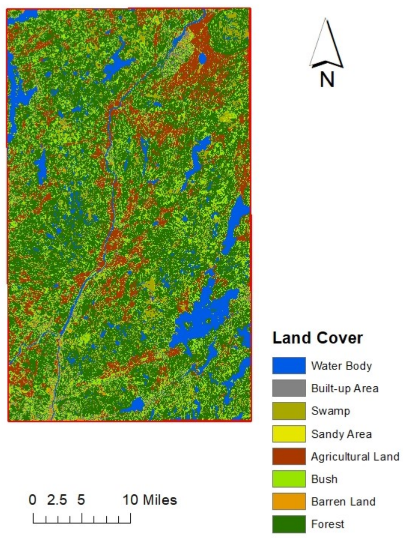
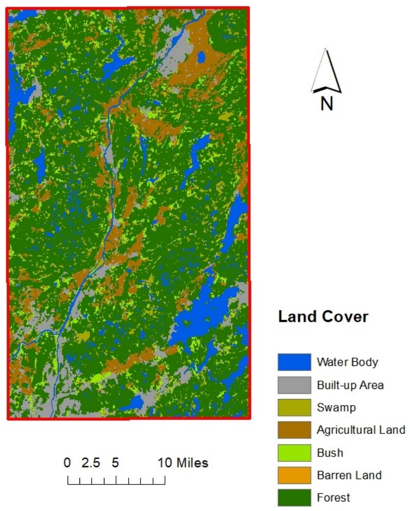


Figure 3.2.16: Land Cover Map of Rwanda

According to the land cover map provided from Lantmäteriet, within Göta river valley, 109 landslides fell into "Agricultural Areas" while 105 landslides are located in "Open Land". 64 landslides occurred in "Forest" and the rest 6 landslides can be seen in "Artificial Areas" and "Wetland". Considering ESRI Global Land Cover Map, 120 landslides occurred in "Crops" while 78 in "Grass" and 59 in "Trees". 22 landslides can be seen in "Built-up Areas" and there are only 4 landslides located in "Shrub". In Rwanda, 15 landslides are located in "Crops". 10 landslides occurred in "Shrub" and 8 landslides in "Trees". Also, 6 landslides were observed in "Built-up Areas".



(a) Land Cover map provided from Lantmäteriet



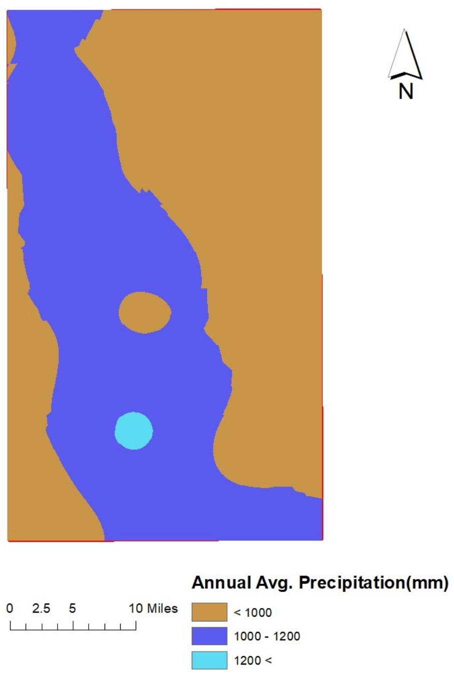
(b) Land Cover map extracted from ESRI Global Land Cover Map

Figure 3.2.17: Land Cover maps of Göta River Valley provided from different data sources

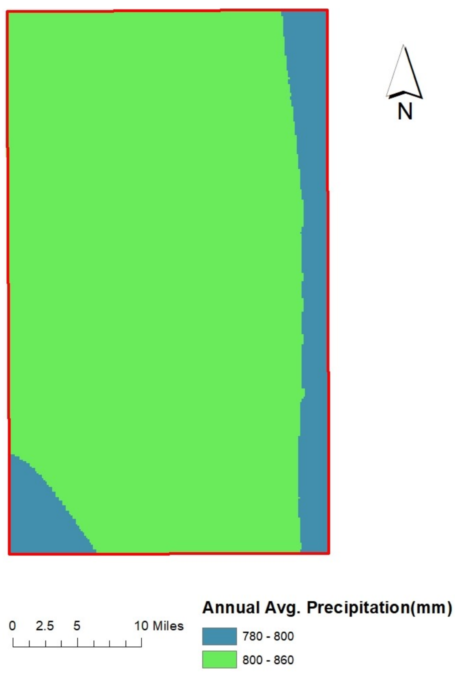
Precipitation

Considering the causes of landslides that have occurred all over the world, it can be said that precipitation is one of the most important factors. Precipitation increases pore water pressure and makes the soil saturated [60]. Therefore, the shear strength of the soil decreases and the slope gets more susceptible for landslide occurrences [54]. Additionally, the floods produced by rainfall can cause shallow landslides [55].

For local data analysis of the Göta river valley, the mean annual precipitation data were provided from the Swedish Meteorological and Hydrological Institute (SMHI) in vector (point) format. This data was rasterized by using IDW interpolation technique within ArcGIS software (Fig. 3.2.18). The most current precipitation data produced by SMHI includes the time range 1991-2020. Therefore this time range was selected for the analysis. For open data analyses, the mean annual precipitation data were extracted from the Global Precipitation Data prepared by the Climate Research Unit of University of East Anglia (Fig. 3.2.18, 3.2.19). The current version of this data was released in 17 March 2021. It contains monthly precipitation information and requires combining them to produce the annual precipitation data. Both local data and global data shows mean annual precipitation for the period from 1991 to 2020. All data (local and open) were classified by using Natural Breaks method. According to the Göta river valley precipitation data provided from SMHI, 105 landslides occurred in the areas with "970-1024mm" annual average precipitation while this is 92 for "905-970mm" and 78 for "1024-1101mm". According to the global precipitation data, 214 landslides occurred in the areas that get "835-861mm" annual precipitation as an average. 67 landslides are located in "812-835mm" and only 3 landslides can be seen within "780-812mm". Within Rwanda 17 landslides were observed in the areas that get "1302-1402mm" precipitation. Number of landslides increased until this point with 3 landslides in "935-1078mm", 5 landslides in "1078-1206mm" and 8 landslides in "1206-1302mm". However, only 6 landslides can be seen in "1402-1575mm".



(a) Precipitation map provided from SMHI



(b) Precipitation data extracted from the global data provided from University of East Anglia

Figure 3.2.18: Precipitation maps of Göta River Valley provided from different data sources for the period 1991 - 2020

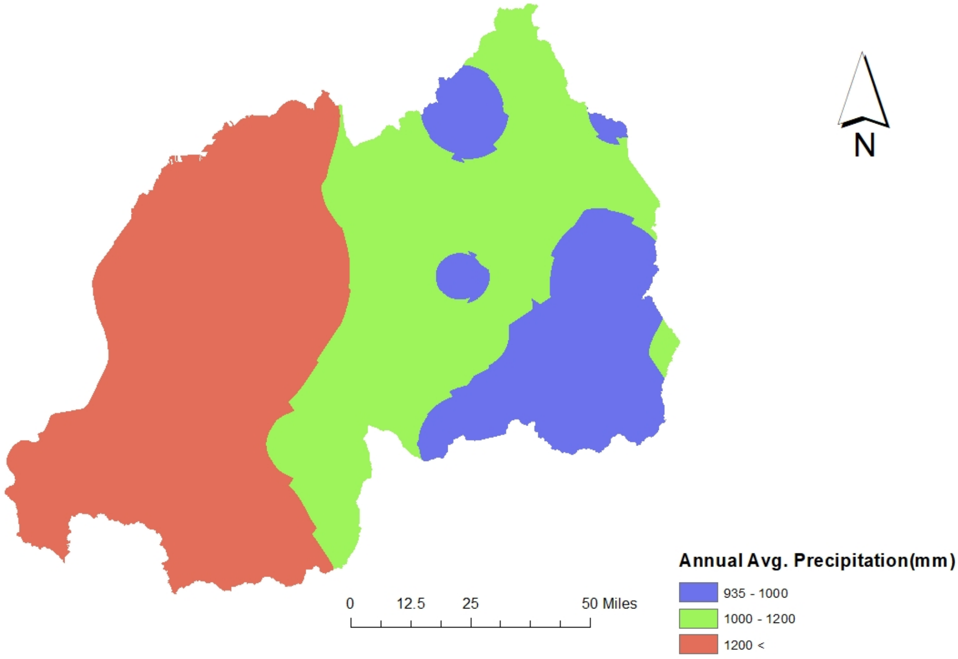


Figure 3.2.19: Precipitation Map of Rwanda for the period 1991 - 2020

Chapter 4

Methodology

4.1 Geographic Information Systems

Geographic Information Systems are a tool used for operating and analyzing geographic data. This data can be such as topographical, geological, human-related statistical or epidemiological data. The main purposes of GIS are decision-making and solving problems that related to geography, by using the data collected from the real world [66]. The areas GIS can be used include; disaster-risk management, natural resource management, land use planning, vehicle routing, telecommunication etc.

GIS is important for disaster-risk management since spatial and temporal variation can be considered. One of the most important advantages of using GIS for disaster-risk management is it allows users to generate alternative scenarios in a spatial context [67]. In landslide susceptibility mapping, it can be used for the analysis of the causative factors [20].

4.2 Multi-Criteria Decision Making

MCDM (multi-criteria decision making) or in some cases MCDA (multi-criteria decision analysis) is a tool for decision analysis and decision making. MCDM theory involves the evaluation of several conflicting criteria when making decisions relating to different fields such as site selection or natural hazard assessment. Even though the problems related to MCDM are common, the existence of MCDM is relatively new [68].

In order to perform a MCDM, a simple but correct model of the environment is required. The model should result in various options and parameters in which the MCDA is used for evaluating multiple conflicting criterias and thus helps to find the best among several alternatives [69]. In order to weigh the different criterias in a proper and correct way, several methods can be used. One of the most common approaches is Frequency Ratio.

4.3 Frequency Ratio

The logic of landslide susceptibility analysis is to assume that landslides occur under specific conditions related to some impact factors [70]. Since Frequency Ratio, as a quantitative method, considers the relationship between spatial distribution of previously occurred landslides and conditioning factors for future landslide prediction [54, 70], it was selected as the main analysis method of this study. Additionally, qualitative methods are difficult to apply in separate study areas [71]. Frequency Ratio is a statistical approach that evaluates the probability of a certain phenomena by calculating the ratio between the density of phenomena in a given class and the density of the same class [72, 73]. It is relatively easier to interpret and understand compared to the other methods [74]. Moreover, it was observed that this method gave more accurate results than the others in the previous studies [23, 75–77].

In the application of the method, conditioning parameters were divided into subclasses, the number of landslide pixels located in each subclass was found for each parameter. Therefore, frequency ratio values were calculated for each subclass. The equation for calculation of frequency ratio is shown below:

$$FR = \frac{N\text{pix}\,(L_{ij})}{N\text{pix}\,(Sij)} \tag{4.1}$$

where $N\text{pix}\,(L_{ij})$ refers to the number of landslide pixels in the jth subclass of factor i and $N\text{pix}\,(S_{ij})$ refers to the number of pixels in the corresponding jth subclass of factor i.

If FR = 1, it is considered as the average value. An FR value higher than 1 indicates a stronger relationship within the factor i and landslides.

Landslide Susceptibility Index (LSI) was acquired by computing the sum of FR values of each subclass within factor i.

$$\text{LSI} = \sum\nolimits_{i=1}^{n} \text{Fr}_i = \text{Fr}_1 + \text{Fr}_2 + \ldots + \text{Fr}_n \tag{4.2}$$

New weights of each subclass were calculated by multiplying the division of the FR value of subclass j to the LSI value of factor i with 100.

$$W_{ij} = 100 \times \frac{FR_{ij}}{LSI_i} \tag{4.3}$$

W_{ij} is the new weight of the subclass j, FR_{ij} is the Frequency Ratio value of the subclass j and LSI_i is Landslide Susceptibility Index value of factor i.

Weights of each conditioning factor were calculated according to the maximum and minimum weights of their subclasses. Finally, the final landslide susceptibility map was prepared by summing up all of the factors by considering weights.

$$\begin{aligned} LSM = \sum FR = (SLP \times w) + (DSR \times w) + (S \times w) + (PRE \times w) \\ +(LC \times w) + (DSD \times w) + (LTH \times w) + (ELV \times w) \end{aligned} \tag{4.4}$$

LSM: Landslide Susceptibility Map, FR: Frequency Ratio, w: Weight of the Factor, SLP: Slope, DSR: Distance to Roads, S: Soil, PRE: Precipitation, LC: Land Cover, DSD: Distance to Drainage, LTH: Lithology, ELV: Elevation.

4.4 Receiver Operating Characteristic

ROC is a common method to compute accuracy rates of the result landslide susceptibility maps. ROC curve is presented in a graph with x and y axis that symbolize 'sensitivity' and 'specificity' [78]. Where, sensitivity stands for the ratio of correctly identified positive observations while specificity is correctly identified negative observations (i.e. sensitivity is the ratio of correctly identified unstable pixels above a desired threshold on the total observed unstable pixels and specificity is the ratio of correctly identified stable pixels below the desired threshold on the total observed stable pixels) [71, 78]. It is possible to use the AUC (Area Under Curve) of ROC curve as a statistical measurement of the accuracy rates of models [78]. The AUC value is equal to the total area of polygons between the thresholds and can be calculated as below;

$$AUC = \sum_{i=1}^{n+1} \frac{1}{2} \sqrt{(x_i - x_{i+1})^2}.(y_i + y_{i+1})^2 \tag{4.5}$$

where x_i is (1-specificity) and y_i is sensitivity at the threshold i when, x_{n+1} = 1 and y_{n+1} = 1.

An AUC value between 0.9 - 1 is considered very high accuracy, while 0.8 - 0.9 is high accuracy, 0.7 - 0.8 is acceptable, 0.6 - 0.7 is low accuracy and 0.5 - 0.6 is very low accuracy [78]. A sample ROC plot can be seen in Fig. 4.4.1:

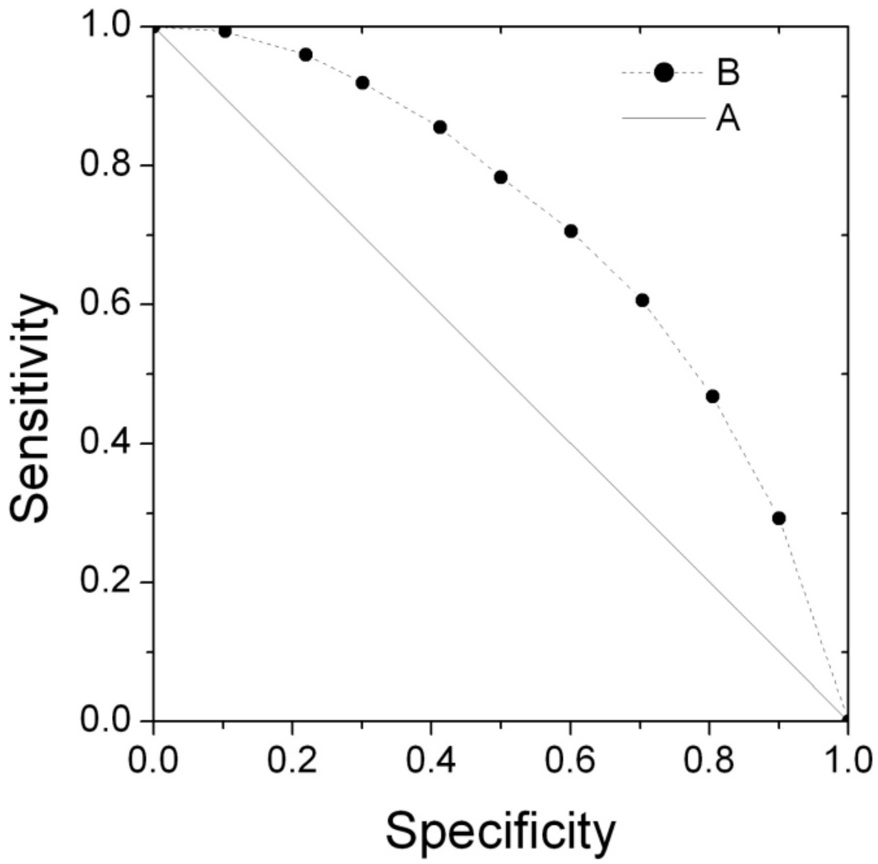


Figure 4.4.1: A sample ROC plot where line A is line of no discrimination (AUC value is 0.5) and line B represents the accuracy of model B with the values of specificity and sensitivity calculated for different thresholds. The AUC value is 0.71 for this graph.
(*Source: https://lup.lub.lu.se/luur/download?func=downloadFilerecordOId=3559066fileOId=3559067*)

4.5 Analysis

The purpose of the literature review was to select the appropriate method and causative factors for landslide susceptibility mapping. After they have been selected and corresponding data were acquired, they were processed for the analysis. The weighting was performed using MCDA - FR technique in a GIS environment. ArcGIS and Microsoft Excel were used as softwares. The comparison parameter maps were first reclassified. For the distance based criteria, 100m, 250m, 500m and 750m were used as reference values. For slope and precipitation, Natural Breaks classification method was used. % 75 (213 points for Göta river valley and 29 points for Rwanda) of the previous landslide locations were randomly selected for the preparation of landslide susceptibility maps and % 25 (71 points for Göta river valley and 10 points for Rwanda) for the validation of the maps. By using the inventory raster maps, tabulation task was performed and frequency ratio values of each class for each criteria were calculated by using the number landslide pixels that each class contains. Therefore, weights of each factor and new weights of each class could be computed. After the final reclassification, the parameter maps were multiplied by their weights and summed up together. A flow chart that represents the process was given below (Fig. 4.1).

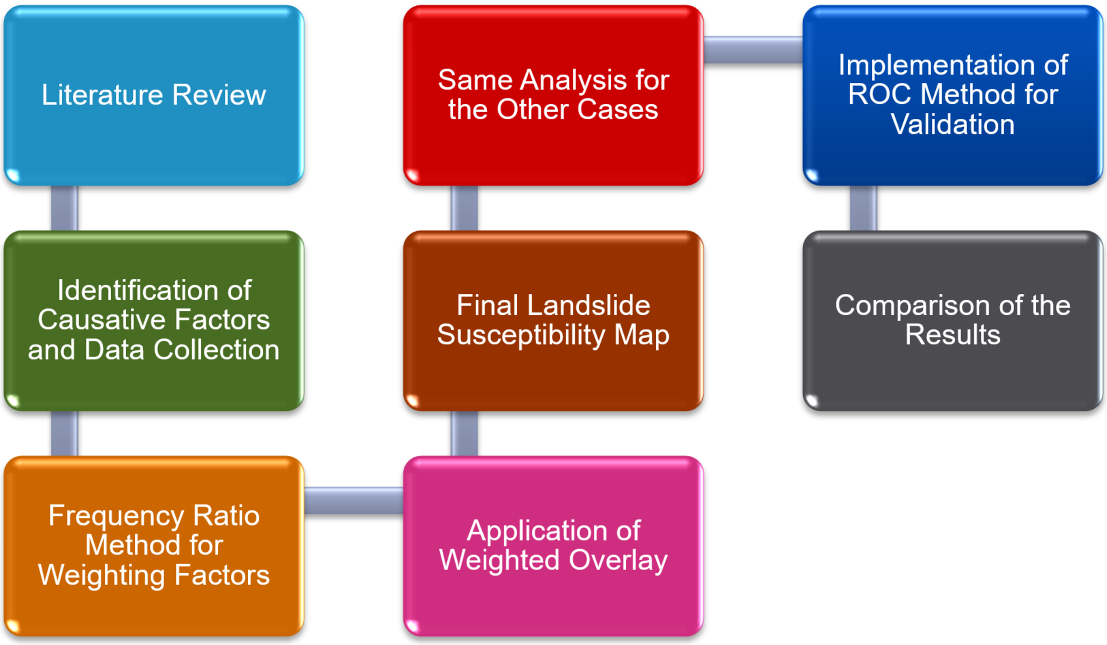


Figure 4.1: Flow chart represents the analysis process.

Table 4.5.1: FR Analysis for Göta River Valley by using Local Data

Factor	Class	Class Pixels (y)	Landslide Pixels (x)	FR (x/y)
Slope	0 - 2	462364	292	0.000631537
	2 - 5	322513	429	0.001330179
	5 - 8	189632	221	0.001165415
	8 - 14	86559	55	0.000635405
	14 - 41	24364	17	0.000697751
Rainfall	798 - 905	190260	15	7.88395E-05
	905 - 970	246826	265	0.001073631
	970 - 1024	359250	242	0.000673626
	1024 - 1101	260118	473	0.001818405
	1101 - 1237	45658	20	0.000438039
Elevation	-0.4 - 34	136625	655	0.004794145
	34 - 68	280044	232	0.000828441
	68 - 98	314800	127	0.000403431
	98 - 133	247230	1	4.04482E-06
	133 - 226	111052	0	0
Land Cover	Wetland	69075	11	0.000159247
	Agriculture	139182	389	0.002794902
	Open Land	110550	276	0.002496608
	Artificial Surfaces	61726	83	0.001344652
	Water	97295	0	0
	Forest	611932	256	0.000418347
Soil Type	Berg	653689	245	0.000374796
	Torv	18377	0	0
	Lera–silt	250316	743	0.002968248
	Vatten	44210	0	0
	Morän	77102	9	0.000116728
	Isälvssediment	31263	5	0.000159933
	Postglacial sand–grus	14804	13	0.000878141
Distance to Drainage	0 - 100	128604	191	0.001485179
	100 - 250	165852	301	0.001814871
	250 - 500	236164	198	0.0008384
	500 - 750	195766	181	0.000924573
	750 - 2400	374918	144	0.000384084
Lithology	Tonalit-granodiorit	554672	806	0.001453111
	Granit	152272	114	0.00074866
	Granodiorit-granit	150242	19	0.000126463
	Paragnejs	73703	61	0.000827646
	Gabbroid-dioritoid	17020	4	0.000235018
	Ögongnejs	24781	11	0.000443888
	Other Rock Types	117070	0	0
Distance to Roads	0 - 100	521100	648	0.001243523
	100 - 250	357743	325	0.000908473
	250 - 500	160212	42	0.000262153
	500 - 750	44706	0	0
	750 - 2559	5999	0	0

Table 4.5.2: Factor and Class Weights for Local Data Göta River Analysis

Factor	Class	Class Weight	Factor Weight
Slope	0 - 2	14	1.60867479
	2 - 5	29	
	5 - 8	26	
	8 - 14	14	
	14 - 41	15	
Rainfall	798 - 905	1	2.72031089
	905 - 970	26	
	970 - 1024	16	
	1024 - 1101	44	
	1101 - 1237	10	
Elevation	-0.4 - 34	79	5.07571872
	34 - 68	13	
	68 - 98	6	
	98 - 133	0	
	133 - 226	0	
Land Cover	Wetland	2	2.473507508
	Agriculture	38	
	Open Land	34	
	Artificial Surfaces	18	
	Water	0	
	Forest	5	
Soil Type	Berg	8	4.213118451
	Torv	0	
	Lera–silt	65	
	Vatten	0	
	Morän	2	
	Isälvssediment	3	
	Postglacial sand–grus	19	
Distance to Drainage	0 - 100	56	1.676938679
	100 - 250	25	
	250 - 500	15	
	500 - 750	0	
	750 - 2400	2	
Lithology	Tonalit-granodiorit	37	2.419166741
	Granit	19	
	Granodiorit-granit	3	
	Paragnejs	21	
	Gabbroid-dioritoid	6	
	Ögongnejs	11	
	Other Rock Types	0	
Distance to Roads	0 - 100	51	3.288500785
	100 - 250	37	
	250 - 500	10	
	500 - 750	0	
	750 - 2559	0	

Table 4.5.3: FR Analysis for Göta River Valley by using Open Data

Factor	Class	Class Pixels (y)	Landslide Pixels (x)	FR (x/y)
Slope	0 - 2	435808	386	0.000885711
	2 - 6	323888	346	0.001068271
	6 - 10	200334	197	0.000983358
	10 - 16	98798	65	0.000657908
	16 - 53	28279	20	0.000707239
Rainfall	780 - 812	16643	34	0.002042901
	812 - 835	21638	315	0.0145577231
	835 - 861	29872	666	0.022295126
Elevation	-13 - 37	140281	666	0.004747614
	37 - 73	294660	229	0.000777167
	73 - 105	316059	119	0.000376512
	105 - 140	236709	1	4.2246E-06
	140 - 239	101941	0	0
Land Cover	Water	102668	3	2.92204E-05
	Trees	666434	217	0.000325614
	Grass	54651	194	0.003549798
	Flooded Vegetation	194	0	0
	Crops	122901	366	0.002978007
	Scrub/Shrub	51409	9	0.000175067
	Built Area	90926	226	0.002485538
	Bare Ground	576	0	0
Soil Type	Podzol	596179	799	0.001340202
	Cambisol	455361	216	0.000474349
	Water	24411	0	0
Distance to Drainage	0 - 100	421383	566	0.001343196
	100 - 250	342113	363	0.001061053
	250 - 500	202202	68	0.000336297
	500 - 750	95922	18	0.000187652
	750 - 2400	36958	0	0
Lithology	Metamorphic	897233	960	0.001069956
	Acid Volcanic	49269	14	0.000284154
	Acid Plutonic	118362	41	0.000346395
	Siliciclastic Sedimentary	5446	0	0
	Intermediate Volcanic	12132	0	0
Distance to Roads	0 - 100	553521	618	0.001116489
	100 - 250	357361	352	0.000984998
	250 - 500	144488	45	0.000311445
	500 - 750	41485	0	0
	750 - 2559	5257	0	0

Table 4.5.4: Factor and Class Weights for Open Data Göta River Valley Analysis

Factor	Class	Class Weight	Factor Weight
Slope	0 - 2	20	1
	2 - 6	24	
	6 - 10	22	
	10 - 16	15	
	16 - 53	16	
Rainfall	780 - 812	5	5.459117623
	812 - 835	37	
	835 - 861	57	
Elevation	-13 - 37	80	8.428868705
	37 - 73	13	
	73 - 105	6	
	105 - 140	0	
	140 - 239	0	
Land Cover	Water	0	3.899954076
	Trees	3	
	Grass	37	
	Flooded Vegetation	0	
	Crops	31	
	Scrub/Shrub	1	
	Built Area	26	
	Bare Ground	0	
Soil Type	Podzol	73	7.743778315
	Cambisol	26	
	Water	0	
Distance to Drainage	0 - 100	45	4.809397857
	100 - 250	36	
	250 - 500	11	
	500 - 750	6	
	750 - 2400	0	
Lithology	Metamorphic	62	6.596898619
	Acid Volcanic	16	
	Acid Plutonic	20	
	Siliciclastic Sedimentary	0	
	Intermediate Volcanic	0	
Distance to Roads	0 - 100	46	4.851334187
	100 - 250	40	
	250 - 500	12	
	500 - 750	0	
	750 - 2559	0	

Table 4.5.5: FR Analysis for Rwanda by using Open Data

Factor	Class	Class Pixels (y)	Landslide Pixels (x)	FR (x/y)
Slope	0 - 5	7665	11	0.001435095
	5 - 11	6915	9	0.001301518
	11 - 18	5023	16	0.003185347
	18 - 27	3907	22	0.005630919
	27 - 55	1765	6	0.003399433
Rainfall	935 - 1078	10241	12	0.001171761
	1078 - 1206	2392	11	0.004598662
	1206 - 1302	4633	6	0.001295057
	1302 - 1402	4276	20	0.004677268
	1402 - 1575	3781	15	0.003967204
Elevation	921 - 1507	10011	8	0.000799121
	1507 - 1733	6365	24	0.003770621
	1733 - 2004	4341	16	0.003685787
	2004 - 2351	2989	12	0.004014721
	2351 - 4500	1601	4	0.002498438
Land Cover	Water	1652	0	0
	Trees	4175	15	0.003592814
	Grass	979	0	0
	Flooded Vegetation	288	0	0
	Crops	6828	19	0.00278266
	Scrub/Shrub	8232	17	0.002065112
	Built Area	3113	13	0.004176036
	Bare Ground	5	0	0
	Snow/Ice	57	0	0
Soil Type	Ferralsol	9450	15	0.001587302
	Lithosol	666	1	0.001501502
	Gleysol	754	0	0
	Andosol	1911	4	0.002093145
	Nitosol	9164	41	0.004474029
	Luvisol	118	0	0
	Water	2206	0	0
	Cambisol	990	3	0.003030303
	Vertisol	71	0	0
Distance to Drainage	0 - 100	10204	35	0.003430027
	> 100	15156	29	0.001913434
Lithology	Unc. Sediments	1057	0	0
	Basic Volcanic	912	7	0.007675439
	Water	991	0	0
	Metamorphic	22481	59	0.002624438
Distance to Roads	0 - 100	20490	61	0.002977062
	> 100	4855	3	0.00061792

Table 4.5.6: Factor and Class Weights for Open Data Rwanda Analysis

Factor	Class	Class Weight	Factor Weight
Slope	0 - 5	9	1.329839733
	5 - 11	8	
	11 - 18	21	
	18 - 27	37	
	27 - 55	22	
Rainfall	935 - 1078	7	1.024839813
	1078 - 1206	29	
	1206 - 1302	8	
	1302 - 1402	29	
	1402 - 1575	25	
Elevation	921 - 1507	8	1
	1507 - 1733	24	
	1733 - 2004	16	
	2004 - 2351	12	
	2351 - 4500	4	
Land Cover	Water	0	1.520201194
	Trees	28	
	Grass	0	
	Flooded Vegetation	0	
	Crops	22	
	Scrub/Shrub	16	
	Built Area	33	
	Bare Ground	0	
	Snow/Ice	0	
Soil Type	Ferralsol	12	1.619736647
	Lithosol	11	
	Gleysol	0	
	Andosol	16	
	Nitosol	35	
	Luvisol	0	
	Water	0	
	Cambisol	23	
	Vertisol	0	
Distance to Drainage	0 - 100	64	2.948185907
	> 100	35	
Lithology	Unc. Sediments	0	3.422560102
	Basic Volcanic	74	
	Water	0	
	Metamorphic	25	
Distance to Roads	0 - 100	61	3.013959291
	> 100	3	

Chapter 5

Results and Discussion

5.1 Landslide Susceptibility Maps

The figures shown below (Fig. 5.1.1, 5.1.2, 5.1.3) represent the final landslide suscptibility maps prepared for Göta river valley and Rwanda country by using local and open data.

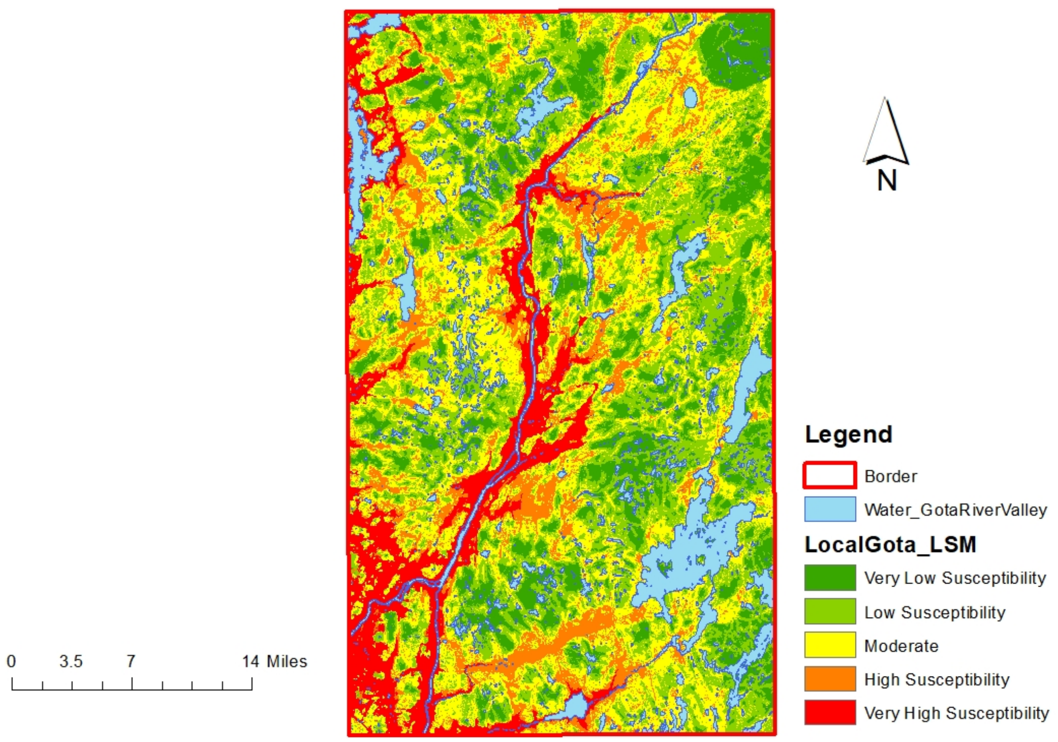


Figure 5.1.1: Landslide Susceptibility Map of Göta River Valley by using Local Data

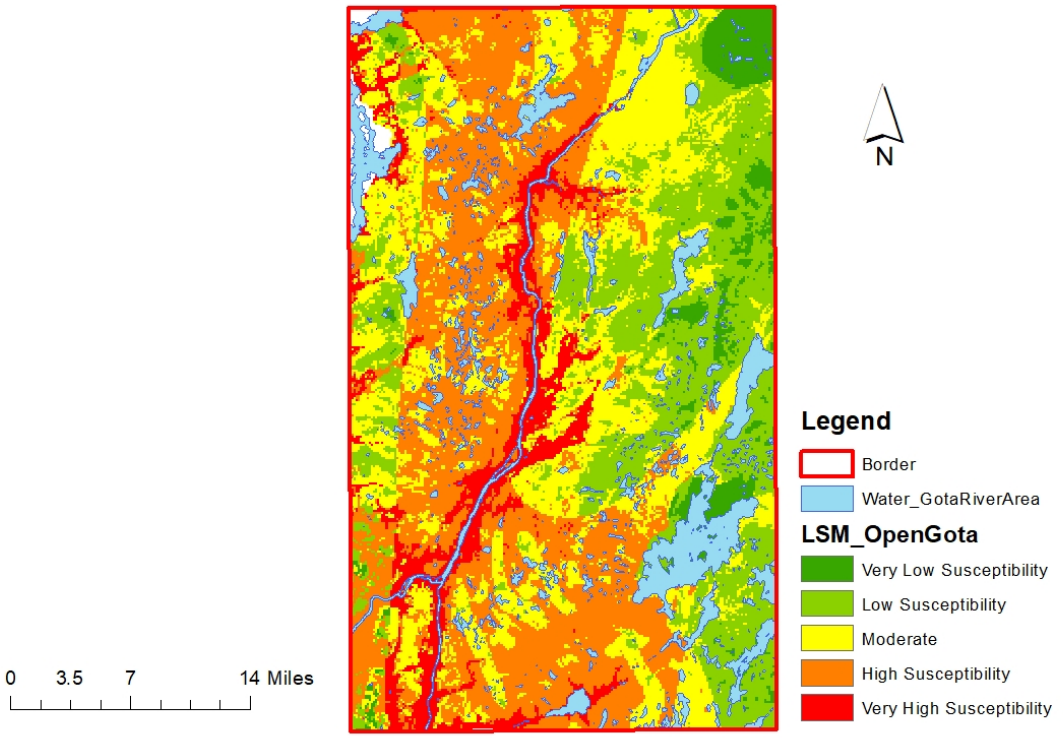


Figure 5.1.2: Landslide Susceptibility Map of Göta River Valley by using Open Data

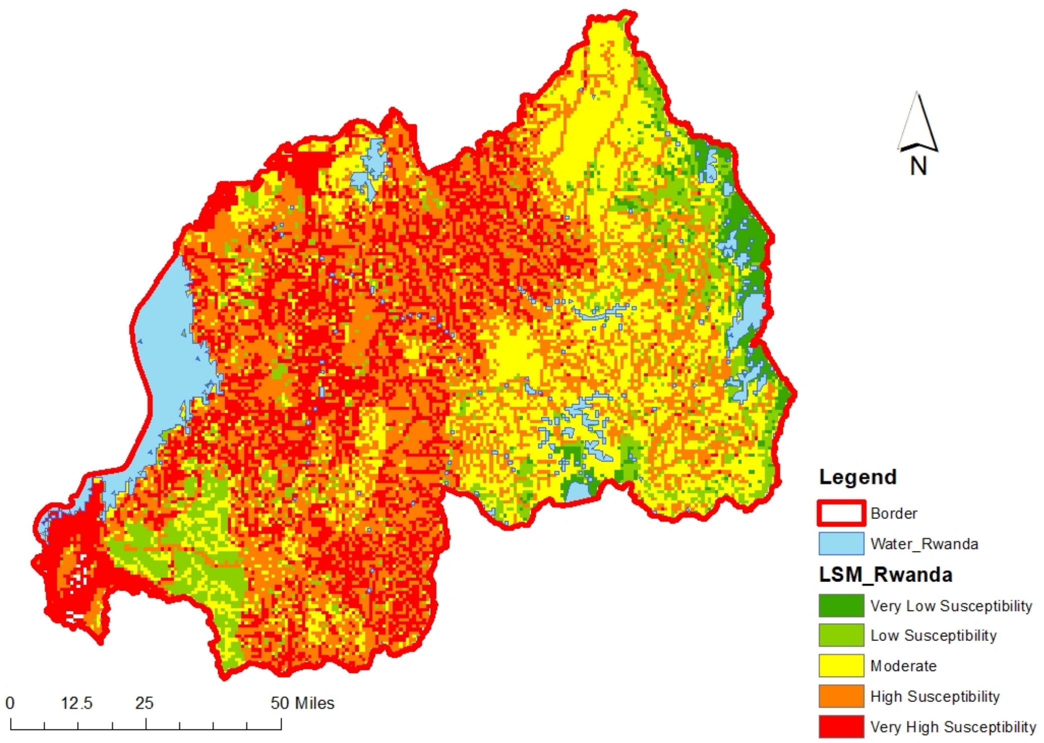


Figure 5.1.3: Landslide Susceptibility Map of Rwanda

5.2 Validation

For the validation of the landslide susceptibility maps, ROC (Receive Operator Characteristic) method was used. In this method, an AUC (Area Under Curve) value closer to 1 is considered as higher accuracy. For Rwanda landslide susceptibility map, test points acquired from NASA Global Landslide Map were used. For Göta river area, previous landslide locations acquired from Lantmäteriet in line format and test points were produced from them. ROC curves of the analysis results can be seen in Fig 5.2.1, 5.2.2 and 5.2.3:

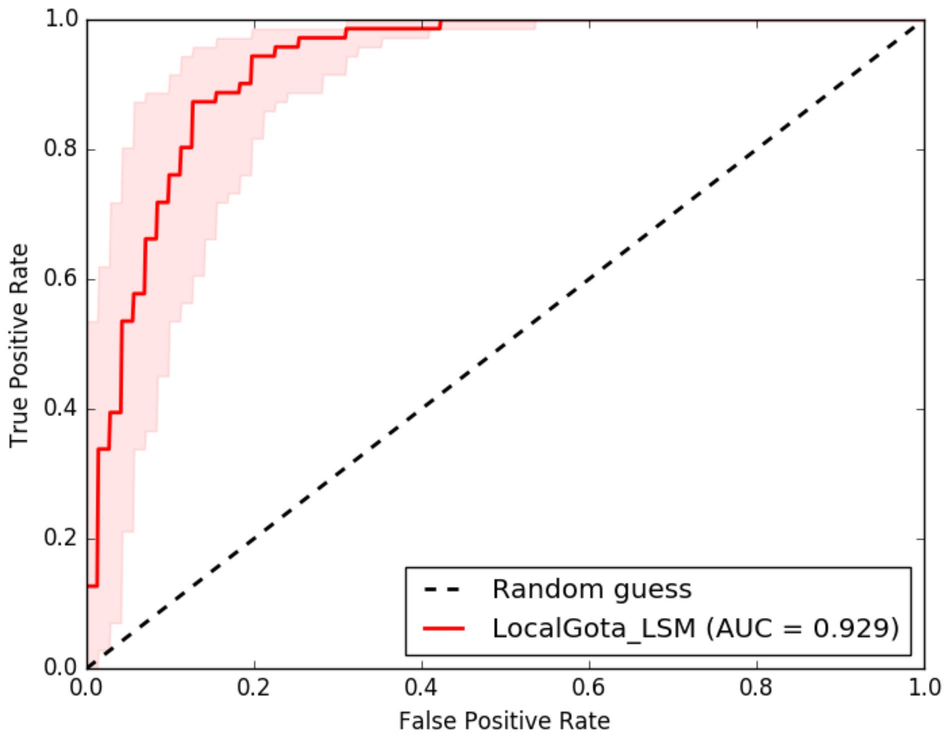


Figure 5.2.1: ROC curve of Göta river valley local data analysis

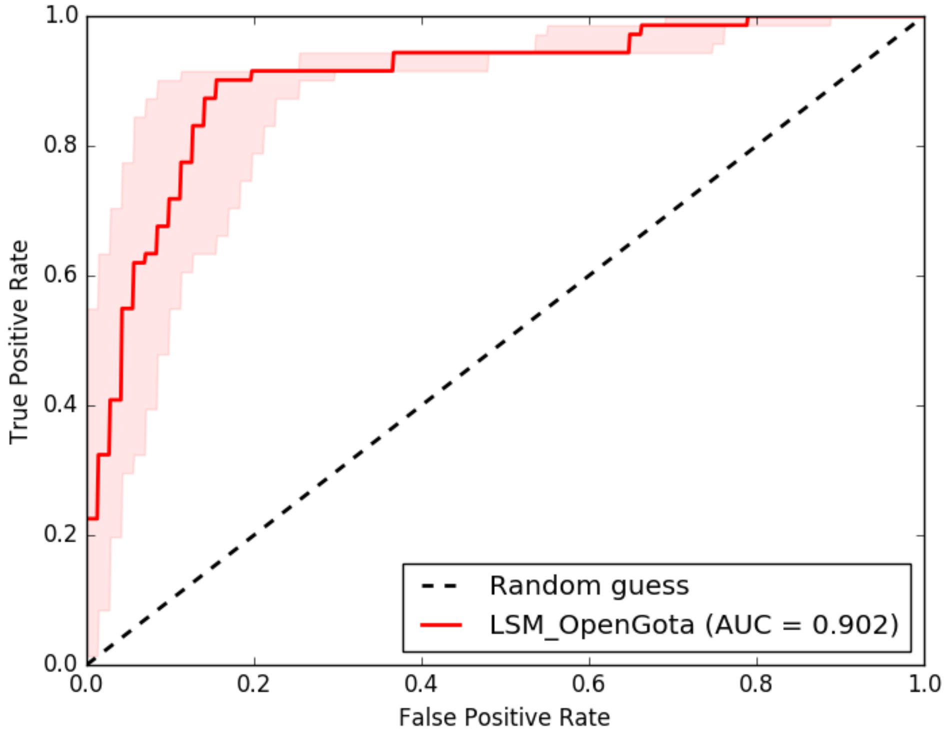


Figure 5.2.2: ROC curve of Göta river valley open data analysis

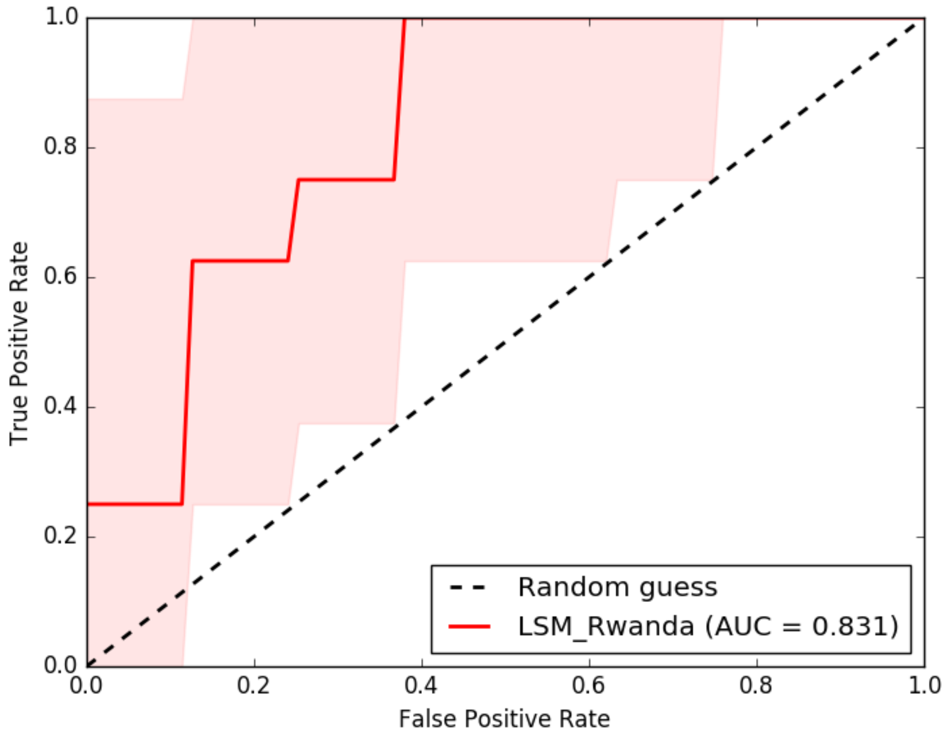


Figure 5.2.3: ROC curve of Rwanda open data analysis

5.3 Discussion

The result maps of local data and open data analyses of the Göta river valley were compared. It was observed that both of the maps indicate very high susceptibility for the buffered area around the river. In the first result map (result of local data analysis), approximately 205 of 284 known landslides fell into the 'very high susceptibility' zones while 61 are located in 'high susceptibility' zones, which together cover approximately 23% of the total study area. These areas are mostly occupied by agricultural fields and have silted and/or clayey soils. Only 14 of known landslides were observed in the 'moderate susceptibility' areas and 4 of landslides fell into the 'low susceptibility' category. For the second result map (result of open data analysis), it was observed that the number of previous landslides located in "moderate susceptibility" category is same with the local data analysis. 5 landslides could be seen in the areas with "low susceptibility". 192 landslides were located in the areas with "very high susceptibility" while 73 landslides were observed in "high susceptibility" category. They together cover around 42% of the total area. It was observed that the areas with 'Podzol' soil type were indicated as 'highly susceptible' or 'very highly susceptible' since soil was one of the most important factors according to the frequency ratio analysis results.

In addition to the Göta river valley comparison, the result map prepared for Rwanda was compared with another Rwanda landslide susceptibility map. The Ministry of Disaster Management and Refugee Affairs of Rwanda prepared a national risk atlas for better assessment of possible future natural disasters. This document also includes a landslide susceptibility map of Rwanda (Fig. 5.3.1). For the preparation of this map, Analytic Hierarchy Process was used as the analysis method. Causative factors selected for the analysis include; lithology, soil type, soil depth, land cover, distance to road, slope, rainfall. Some differences can be seen between the result maps of the two different analyses. Since data sources are different than the ones within this study, it can affect the result landslide susceptibility map. It was observed that the Rwanda result map of this study indicates more areas as susceptible. However, both maps shows western part of the country as more susceptible. There are some areas that were shown as lowly susceptible in the result map within National Risk Atlas, however, shown as moderate in the result map of this study. Additionally, in the western part of the country, some areas were shown as moderate within the map of the atlas, however, shown as highly susceptible in the result map of this study. This can depend on the way of classification of the maps. In this study, Natural Breaks method was used for classification of the result maps.

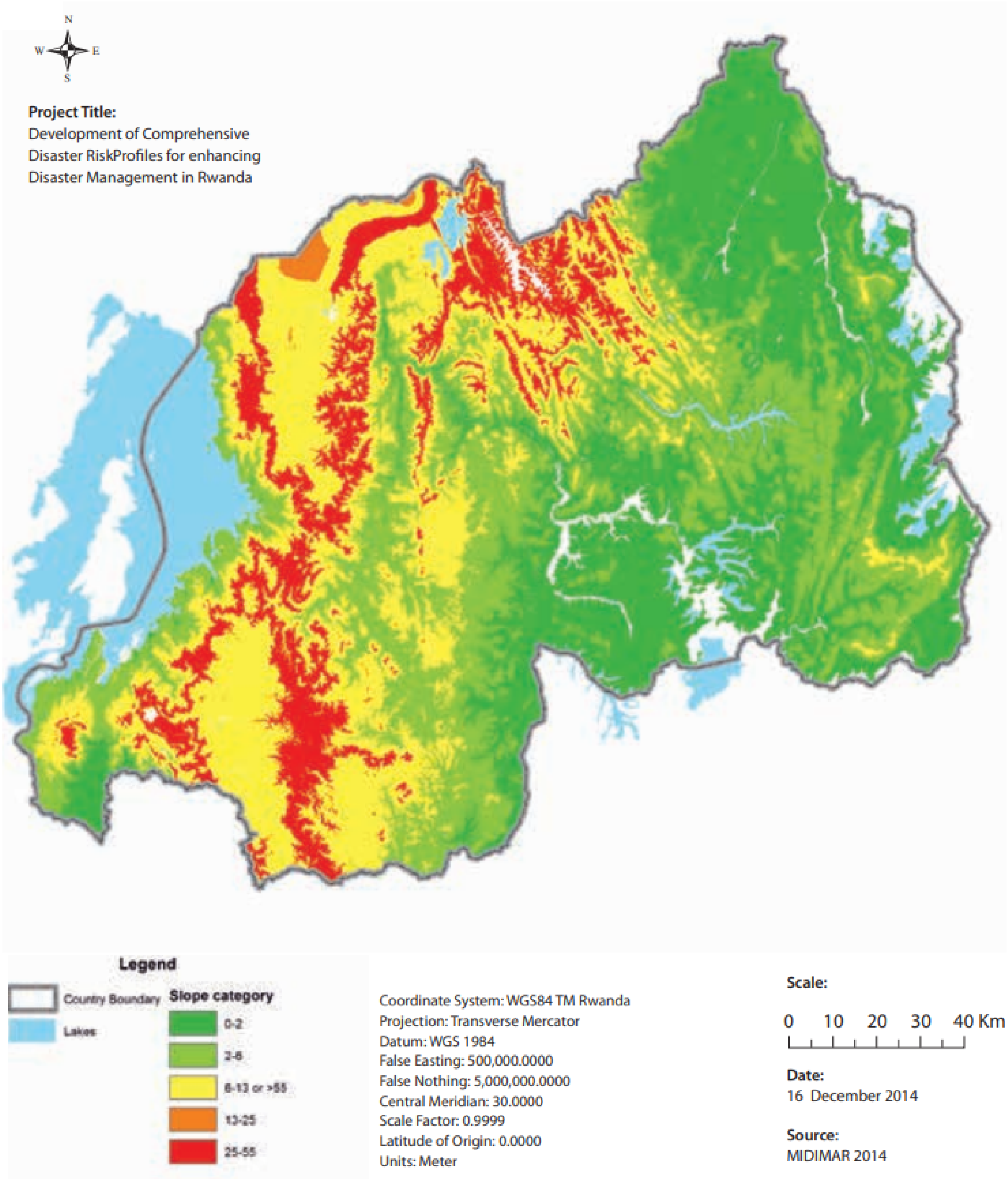


Figure 5.3.1: Landslide susceptibility map of Rwanda prepared by the Ministry of Disaster Management and Refugee Affairs of Rwanda
(*Source: https://www.gfdrr.org/en/publication/rwanda-national-risk-atlas*)

Moreover, since the methods used for the analyses have different approaches (heuristic and statistical), opinions of experts and locations of previous landslides may lead to some differences within the results. The landslide inventory used in the analysis of Rwanda, within this study is not complete. Therefore, another comparison is necessary when it is possible analyze and validate the area with a complete landslide inventory.

During the analysis, it was observed that open and local elevation data of Göta river valley were nearly same. With respect to precipitation, there were not significant difference between the two sources, however the interval of the local precipitation data was wider. Although the land cover provided from Lantmäteriet has more details than the map extracted from ESRI global land cover map, it includes subclasses of main land cover classes which need to be generalized for the analysis. Therefore, the land cover maps were relatively similar. Additionally, the drainage and road maps were nearly same. Lithology and soil maps were the main differences between open/local analysis of the study area. According to the result maps, it can be seen that soil type was the main parameter that made the main difference between the analyses of the Göta river valley. The local soil map used in this analysis was generalized by SGU, however a non-generalized map also exists. It has 144 soil classes and some part of the map is shown below (Fig. 5.3.2):

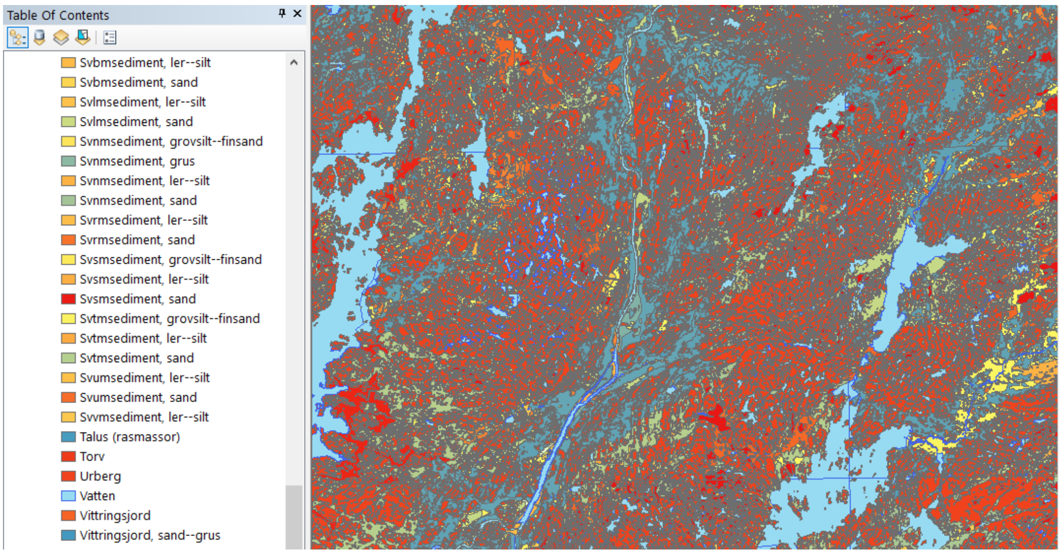


Figure 5.3.2: Detailed Soil Map of Göta River Valley

By using the satellite images provided from Google Earth Pro software (Fig. 5.3.3, 5.3.4, 5.3.5), it was observed that highly susceptible areas mostly consist of agricultural fields for both of the study areas. In addition to this, it could be seen that there are some settlements located in highly susceptible areas within Rwanda. Moreover, these areas have very high slope angles, compared to the areas within Göta river valley.

Figure 5.3.3: It was observed from the satellite view that highly susceptible areas in Göta river valley mostly consist of agricultural fields

Figure 5.3.4: Satellite view shows that agricultural fields and settlements form highly susceptible areas in Rwanda

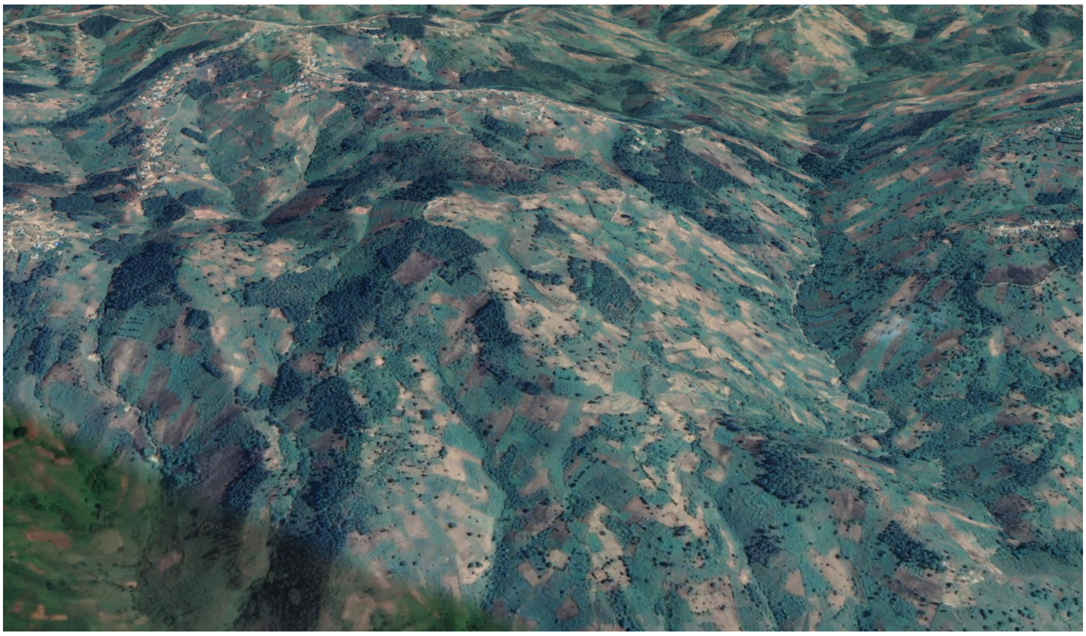


Figure 5.3.5: 3d view shows that highly susceptible areas in Rwanda have very high slope degrees

Chapter 6

Conclusion and Future Work

In this study, the performance of publicly available geospatial data was investigated for landslide susceptibility analysis by comparing it with the data provided from several public institutions of Sweden. To ensure the performance of the analysis, another area that has no available local geospatial data was analyzed afterwards. A statistical method, Frequency Ratio, was used for the implementation. 8 conditioning parameters were selected for the analyses; elevation, soil type, slope, precipitation, land cover, distance to drainage network, lithology, distance to roads. Since there is still not a clear explanation related to the relationship between the pixel size of the input maps and the accuracy level of the analysis, spatial resolution issue was ignored in this study. 50m x 50m spatial resolution was used for all of the analyses. Two areas were selected as study area; Göta river valley (Västra Götaland, Sweden) and Rwanda.

For the validation of the produced maps, the ROC method was implemented by using testing inventory landslide points. %75 of inventory data were randomly selected for preparation of landslide susceptibility maps while %25 were kept for the validation of the result maps. The AUC graphs showed that local data Göta river valley analysis map has the highest accuracy (% 92.9) with greater Area Under Curve, followed by Göta river valley (% 90.2) and Rwanda (% 83.1) analysis maps produced by applying open data. There is % 7 difference between the accuracy rates of open data Göta and Rwanda result maps (% 90.2 and % 83.1). It was considered that the landslide inventory affects the results and accuracy levels since it is necessary to use it for both training and testing. Also, the result curve of Rwanda analysis seems different than Göta river area result curves. The reason is there are fewer previously occurred landslide points used for Rwanda analysis, compared to Göta river area (39 vs 284).

The factors used in the analyses did not have the same importance levels for the study areas. Slope angle was not a critical triggering factor for the Göta river valley, while, it was more effective on Rwanda. In the Göta river valley, most of the landslides have occurred in the areas with 0° - 6° slope angle. In Rwanda, the areas that have a slope angle between 11° - 28° have experienced more number of landslides, compared to the other areas. It was observed that, in the Göta river, the number of landslides increases until 1100 mm annual rainfall. In Rwanda, there is not a regular increase in the number of landslides with the increase in the amount of rainfall. Most number of landslides were observed in the areas that have 1302 - 1402 mm annual rainfall, however, there is less number of landslides observed in the areas that have 1402 - 1575 mm annual rainfall. Land cover was not a decisive factor for Rwanda as ’Trees’, ’Crops’, ’Shrub’ and ’Built Area’ classes have approximately same number of landslides. In the Göta river valley, it was observed that landslides occurred more in the agricultural areas, compared to the other areas. Soil type was not a critical factor for Rwanda analysis as it was for Göta river valley analyses. ’Silted-clayey’ soil was the most landslide susceptible soil type for local data analysis of Göta river valley while it was ’Podzol’ and ’Nitosol’ for open data analyses of Göta river valley and Rwanda. Considering elevation, different results were provided from the study areas. In the Göta river valley, it was observed that most of the landslides occurred in the areas with less than 40 meters elevation. In Rwanda, most of the landslides are located in 1500 - 1730 meters interval. Lithology was important for both of the study areas. Within Göta river valley, most of the landslides are located in the areas with ”tonalit-granodiorit” rock type according to the local lithology data, while it was ”metamorphic rocks” for both of the open data analyses. Regarding the distance based factors, it can be seen that more landslides occurred in the 100 meter buffered area of drainage network and roads.

By using the satellite images provided from Google Earth Pro software, the areas with high landslide susceptibility were observed. It could be seen that the highly susceptible areas within Rwanda have very high slope angles. However, this is not the case for the Göta river valley, according to 3d visualization and slope angle map of the area. More susceptible areas have less slope angles in Göta river valley. Since ”soil type” is one the most important conditioning parameters according to the Frequency Ratio analysis, it was assumed that the landslides previously occurred in this area were most likely related to the soil type ”Silted-clayey”. In addition to this, it can be seen that there are many residences located in highly susceptible areas within Rwanda. This situation requires more serious precautions in Rwanda to avoid damages on human lives as a result of possible future landslides.

The most important disadvantage of open data landslide susceptibility analysis is landslide inventories. Currently, the only open source landslide inventory map is Global Landslide Map of NASA and it does not include all of the landslides occurred. Therefore, it does not allow researchers to do small-scale regional analyses. Alternatively, other methods can be applied that do not require training and testing data (e.g. Analytic Hierarchy Process) when there is not available inventory data for the study area. It was observed that usage of local data is beneficial when it comes to the parameters such as soil type, lithology and land cover since local institutions focus on specific areas within the country and prepare more detailed maps. The data that were produced from digital elevation models can be easily replaced with local data.

In the future studies, the other methods can be applied to the same study areas to compare local and open data performances as it is necessary to validate the results with other methods. Different factor combinations can be used with the same method and study areas to see the effect of causative factors on the accuracy level of landslide susceptibility maps. Since there is not an alternative globally available inventory data, it can be useful to try another inventory data for Rwanda, provided from local institutions to see the changes in the performance of the analysis. Moreover, other open data sources can be used as an alternative.

Consequently, although it is preferred to use the data provided from local institutions, it was observed that globally available open data demonstrate strong potential for landslide susceptibility mapping when high-resolution local data are not available. Usage of open data can help for better decision making especially in low and middle income countries and it can be possible to reduce damages from future landslides in these countries.

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